Cityscape

A Journal of Policy Development and Research

COVID-19 and the Housing Markets
Volume 24, Number 3 • 2022

U.S. Department of Housing and Urban Development Office of Policy Development and Research

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Introduction

The onset of the COVID-19 pandemic disrupted society in a multitude of ways. In the United States, cases rose quickly and spread across the country in early 2020, which led to the declaration of a national emergency in March 2020. Local governments imposed lockdowns and began quarantine mandates that would partially conclude by that summer but restart multiple times over the next couple of years.[1]

Various federal agencies enacted policies to promote the safety and soundness of their mission-driven activities. A challenge that arose in those early days was tracking how rapidly changing health concerns might lead to economic and prudential risks. Strong housing markets granted early and necessary stability for wavering macroeconomic conditions. An economic crisis was averted by providing debt payment relief and large-scale injections of financial liquidity. However, as conditions improved, other economic and sociopolitical dilemmas challenged decisionmakers to consider whether it was possible to return to prior circumstances or if we faced adapting to a "new normal."

This symposium of *Cityscape* is devoted to COVID-19-related changes in the U.S. housing markets, and whether the current trends merely build on prepandemic tendencies or represent a regime change. The articles show that COVID-19 has created unique challenges for data collection, measurement, and trend analysis. Each article documents changes in the practical analysis of real

[1] At the time of this writing, in the United States, more than a million people have died from the disease, and more than 86 million positive cases have been identified, representing one-fourth of the country's population. The number, though, has become increasingly censored as vaccines and therapies have reduced side effects, at-home testing has expanded and reduced reporting to public authorities, and data collection has become less frequent and less detailed.

estate markets. The authors of these contributions work for different federal agencies focused on consumer protections, housing markets, secondary mortgage lending, and regulatory oversight.

Symposium Articles

Credible, accurate, and objective statistical information is important for evidence-based policymaking. The pandemic has disrupted many aspects of our society, and—although less tangible—housing and mortgage market data and research insights have helped provide stability during the otherwise uncertain times since COVID-19 began. This symposium includes six articles that survey how both public and private sectors have reacted to the changes in underlying forces of housing supply and demand.

The initial three articles cover how mortgage markets have survived in terms of both preventing large-scale defaults by mortgage borrowers and ensuring stability in the lending environment. The subsequent three articles review how housing markets have been affected by rising prices, tighter supply, and relocations spurred by the pandemic and remote work.

In the first article, "Characteristics of Mortgage Borrowers During the COVID-19 Pandemic: Evidence from the National Mortgage Database," Greta Li, David Low, and Judith Ricks (2022) present evidence about who took advantage of forbearance, which gave homeowners a temporary pause on mortgage payments. The authors investigate the characteristics and demographics of individuals, finding that minority and lower-income households were more likely to be in forbearance or delinquent up to a year after the pandemic began.

In the second article, "Heterogeneity in the Effect of Covid-19 Mortgage Forbearance: Evidence from Large Bank Servicers," Lan Shi (2022) investigates the next step in the process when borrowers try to transition out of forbearance. Data from the largest national bank servicers suggest that borrowers take several distinct exit paths when their forbearance period is completed. Some borrowers signed up but did not need "the call option," in which they could choose to stop paying on their mortgage without suffering a negative mark on their credit report or fear of losing their home. These borrowers either remained current throughout forbearance or—if not all payments were made—they were still able to become current upon exit. Other borrowers, though, were not as fortunate and encountered personal financial difficulties that left them unable to continue making the same mortgage payment. They may have required modifications or found themselves back in forbearance after having successfully exited and resumed their regular payments. The forbearance policy served various purposes depending on borrower-specific situations, such as providing an opportunity to improve financial liquidity and reducing uncertainty in sensitive labor market conditions.

In the third article, "Mortgage Appraisal Waivers and Prepayment Speeds," Joshua Bosshardt, William Doerner, and Fan Xu (2022) study a policy change to appraisal waivers during the early stages of the pandemic. The adjustment aligned eligibility and expanded waivers so that Freddie Mac-refinanced loans would be treated similarly to those delivered to Fannie Mae. Prepayment rates appear to increase, but the rise is largely attributable to loans with waivers tending to self-select as already having faster prepayment speeds. A year later, this impact began to abate as mortgage rates rose and began to phase out borrowers who would have previously benefited financially from refinancing at the historically low rate levels. The decline in refinance activity coincided with the slowdown of appraisal waivers, which had been driven by those mortgage product types, and fewer differences remained between the Enterprises for loans eligible for the waivers.

In the fourth article, "Applying Seasonal Adjustments to Housing Markets," William Doerner and Wenzhen Lin (2022) confront an issue in the measurement of house price indices. These indices are adjusted to remove usual seasonal effects. Doerner and Lin start by describing how adjustment factors are usually calculated with simulations and empirically. Extremely rapid off-season appreciation during the pandemic has played havoc with these models.

In the fifth article, "Housing Supply and Liquidity in the COVID-19 Era," Justin Contat and Malcolm Rogers (2022) turn to the first stage of house price formation, when properties are listed for sale. High-frequency real estate listings data suggest that statistically significant structural breaks in the supply and liquidity of housing markets occurred during the spring of 2020 and continued throughout that year for a variety of housing market indicators. The authors pose the question of how such breaks may vary and change by location.

In the sixth article, "Are Settlement Patterns Changing in the United States as We Emerge from the COVID-19 Pandemic?" Elaine Ng, Jeremy Albright, Holi Urbas, and Kurt Usowski (2022) describe a change in housing settlement patterns during the pandemic. The authors use urban theory to explain potential relocation patterns in homeownership and rental activity during the pandemic with four typologies: cities remain the same due to agglomeration spillovers, intermediate cities develop as the demand for physical proximity relaxes, inner-city areas are hollowed out like a donut as preferences shift, or urban cities vanish as bid rent curves flatten with the diminished competition. Data suggest there is evidence that each of these transitions happened in different areas of the country, but the trends may have begun to slow. These findings contrast with popular press articles, which make simple assertions of a single settlement pattern—a mass exodus from cities. The results highlight the potential but still unknown extent to which the pandemic has altered housing markets.

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Guest Editors

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Characteristics of Mortgage Borrowers During the COVID-19 Pandemic: Evidence from the National Mortgage Database

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Abstract

Using a nationally representative sample of first-lien mortgages, this article analyzes borrower and mortgage characteristics of borrowers that were in forbearance during the COVID-19 pandemic. The analysis shows that Black and Hispanic borrowers were severely overrepresented among borrowers in forbearance compared with their representation in the overall sample. This article also sheds light on the potentially difficult financial circumstances of borrowers that entered into forbearance, especially those who remained in forbearance after the expiration of CARES Act protections. The analysis provides a descriptive baseline that is useful for understanding the effects of pandemic mortgage policy on borrower transitions out of forbearance programs.

Introduction

The COVID-19 pandemic created widespread and severe financial hardship among homeowners. Almost 8 million homeowners took advantage of mortgage forbearance programs designed to provide financial relief over the course of the pandemic (Black Knight, Inc., 2022). Forbearance programs, such as those provided under the Coronavirus Aid, Relief, and Economic Security Act (CARES Act) in March 2020, allowed many borrowers to take forbearances for reasons related to the COVID-19 pandemic for periods lasting up to 18 months.[1] A significant number of homeowners have transitioned out of those forbearances over the past year due, in part, to improving economic conditions and the expiration of protections under the forbearance programs for many loans beginning in the fall of 2021. Given these changes, the goal of this article is to better understand the characteristics of borrowers who remain in forbearance.

Using data from the National Mortgage Database (NMDB®),[2] this article reports on the characteristics of mortgage borrowers during the COVID-19 pandemic. The NMDB is a random 1-in-20 sample of closed-end first-lien mortgages in the United States that provides rich detail on the borrower's account status and characteristics. The account status in the NMDB is based on credit record data (Durbin et al., 2021).[3] The authors analyze borrower demographics and loan characteristics for a sample of open mortgages from March 2021 and a second sample from January 2022. For more details on these samples, see Durbin et al. (2021) and Li and Ricks (2022). Overall, the January 2022 sample of borrowers had a forbearance rate of 1.3 percent,[4] compared with 4.7 percent in the March 2021 sample.

First comes a discussion on the changes in forbearance rates between March 2021 and January 2022. The share of mortgages in forbearance fell significantly for both minority and non-minority borrowers between March 2021 and January 2022. Decreases in the rate of forbearance were relatively larger for non-White than for White borrowers, with the largest decreases occurring among Hispanic and other-race borrowers.

Then, this article examines the cross-sectional differences in borrower characteristics. In the January 2022 sample, Black and Hispanic borrowers were overrepresented among those in forbearance. Black and Hispanic borrowers accounted for a combined 31.2 percent of forbearances while accounting for only 18.2 percent of the overall sample of borrowers. Furthermore, Black borrowers were 2.8 times more likely and Hispanic borrowers were 1.6 times more likely to be in forbearance than White borrowers.

Next, borrowers in forbearance as of January 2022 seem to have less financial capacity, on average, than borrowers in forbearance as of March 2021. Among mortgage borrowers who were delinquent pre-COVID-19, the rate of forbearance fell 46 percent between March 2021 and January 2022, whereas the rate of forbearance fell 74 percent over the same period for borrowers who were current pre-COVID-19. In addition, mortgage borrowers who were delinquent pre-COVID-19

[1] Under the CARES Act, homeowners with a GSE (Fannie Mae and Freddie Mac) and other federally backed mortgages have the right to request and obtain a forbearance for up to 180 days and an extension for another 180 days (for a total of 360 days). Guidance from the GSEs and federal agencies allows up to 18 months of forbearance. Privately owned mortgages are not covered by the CARES Act, but many servicers and investors offer similar protections for those loans.

[2] See National Mortgage Database Program, Federal Housing Finance Agency. https://www.fhfa.gov/PolicyProgramsResearch/Programs/Pages/National-Mortgage-Database.aspx.

[3] The measurement of forbearance and delinquency in credit reporting has some limitations. For a detailed discussion of these limitations, see Durbin et al. (2021), which explains issues with the measurement of forbearance and delinquency in credit reporting data.

[4] The January estimate is smaller than publicly available estimates provided by Black Knight through the middle of January, which indicate that 1.6 percent of borrowers were in forbearance programs (Black Knight, Inc., 2022). This difference is likely due to differences in the underlying data used to estimate forbearance. Black Knight uses daily mortgage servicing data, which do not experience a lag in the reporting of account status as is the case in credit reporting data.

were relatively less likely to be in forbearance in January 2022 compared with borrowers that were current pre-COVID-19. Pre-COVID-19 current borrowers were 12.4 times more likely to be in forbearance than to be 60+ days delinquent. In comparison, pre-COVID-19 delinquent borrowers were only 2.7 times as likely to be in forbearance than to be 60+ days delinquent.

The final discussion focuses on cross-sectional differences in the current (or mark-to-market) loan-to-value (LTV) ratio. Mortgage borrowers with current LTV ratios over 95 percent had significantly higher rates of forbearance as of January 2022 compared with loans with lower LTV ratios. However, this population of borrowers accounted for a small share of forbearances (1.0 percent). Finally, a significantly smaller share of loans in the January 2022 sample had current LTV ratios above 80 percent relative to the March 2021 sample of borrowers. Unlike in past recessions when house prices fell, during the pandemic, house prices increased significantly, reducing borrowers' LTVs.

An important caveat to this analysis is that this article focuses on comparing borrowers in forbearance to those not in forbearance. The authors do not study how those entering (or exiting) forbearance differ from others or the different ways borrowers can exit forbearance. For more information on these topics, see Shi, 2022.

Borrower Demographics

In this section, the authors analyze the demographics of mortgage borrowers who were in forbearance as reported through January 2022. An earlier related report by Durbin et al. (2021) showed that minority borrowers made up a disproportionately larger share of borrowers with loans either in forbearance or delinquent compared with the overall population of mortgage borrowers, using a March 2021 sample of borrowers. In particular, minority borrowers and borrowers living in majority-minority tracts had a higher likelihood of being in forbearance than White borrowers and borrowers not in majority-minority tracts, respectively. As shown in exhibit 1, although fewer loans to minority borrowers and loans for properties in majority-minority tracts were in forbearance in January 2022 compared with March 2021, these borrowers continue to be overrepresented among borrowers in forbearance.

Forbearance rates have fallen for all groups when broken out by race and ethnicity. Roughly 1.1 percent of White borrowers were in forbearance as of January 2022, compared with 3.7 percent in March 2021 (a 71-percent decrease). Black borrowers had forbearance rates of 3.0 percent (68-percent decrease). Roughly 1.7 percent of Hispanic borrowers were in forbearance in January 2022 (an 80-percent decrease), and all other borrowers[5] had forbearance rates of 0.9 percent (an 84-percent decrease). These numbers represent significant reductions in forbearance for minority groups, especially Hispanic and other-race borrowers, that are relatively larger than for White borrowers.

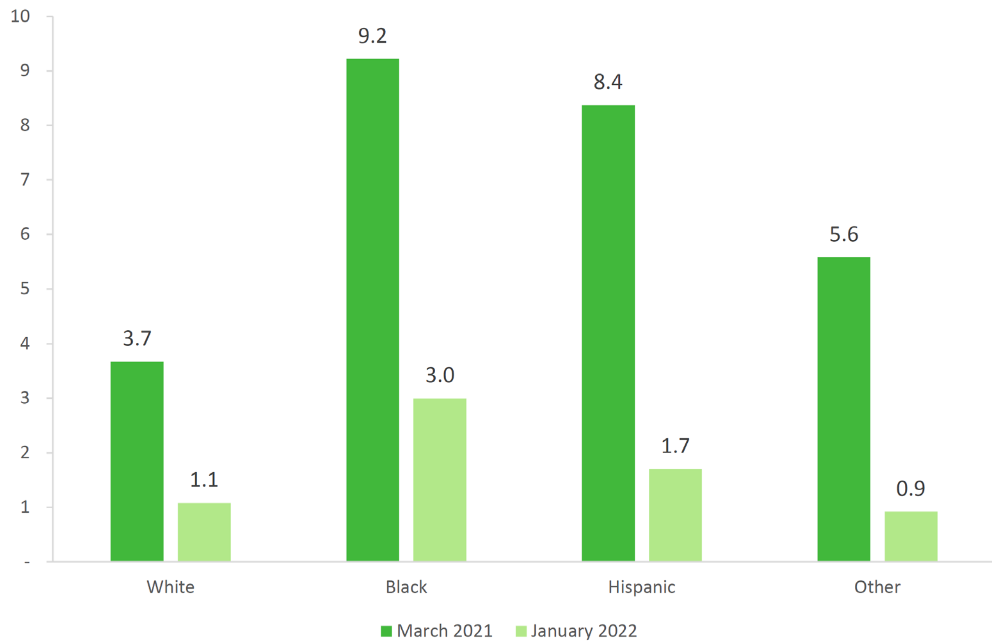
Nevertheless, Black and Hispanic borrowers remained significantly more likely to be in forbearance compared with White borrowers. Black and Hispanic borrowers were 2.8 times and 1.6 times more

[5] As in Durbin et al. (2021), the other-race borrower group includes non-Hispanic borrowers reported as American Indian, Asian, Native Hawaiian/Pacific Islander, or multiple races.

likely to end up in forbearance than White borrowers, respectively. Other-race borrowers were less likely to experience forbearance compared with White borrowers.

Exhibit 1

Percentage of Borrowers in Forbearance by Race and Ethnicity



Source: National Mortgage Database Program, Federal Housing Finance Agency and Consumer Financial Protection Bureau

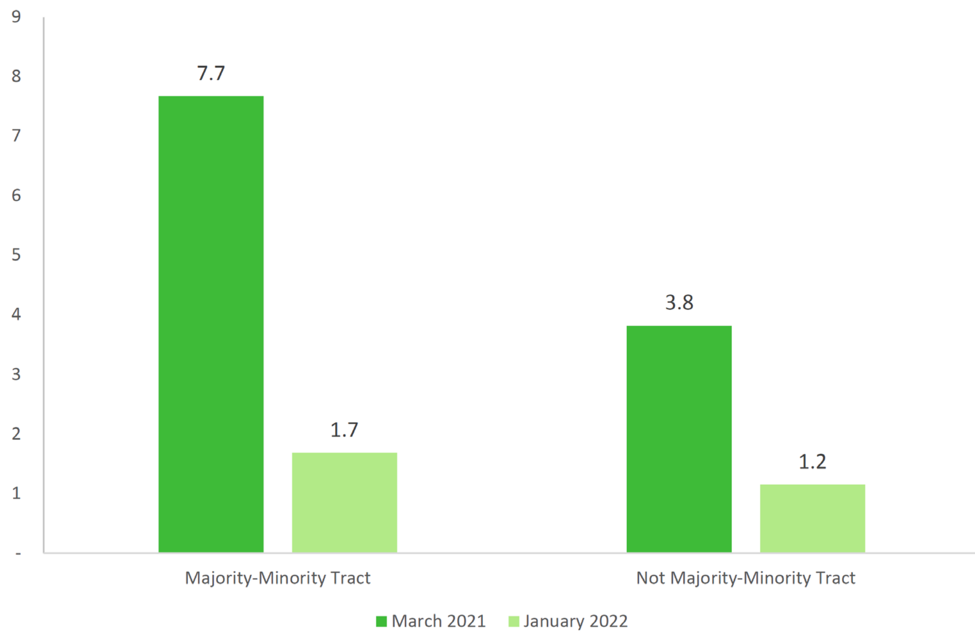
Considering the overall composition of loans that were in forbearance in the January 2022 sample, White borrowers accounted for roughly 64 percent of loans in forbearance, whereas Black and Hispanic borrowers each accounted for roughly 16 percent and other-race borrowers accounted for roughly 4 percent. Loans held by White borrowers continued to make up a large majority of this group, consistent with White borrowers accounting for the largest share of mortgages in the sample.[6] In January 2022, the share belonging to Hispanic borrowers fell, and the share belonging to Black borrowers increased relative to March 2021. The different pattern for Black borrowers results from having a relatively smaller reduction in forbearances since March 2021 while accounting for a relatively smaller share of the overall sample compared with Hispanic borrowers.

Turning to analysis at the tract level, borrowers living in majority-minority census tracts remained more likely to be in forbearance, as shown in exhibit 2. The data show that roughly 1.7 percent of borrowers living in majority-minority tracts were in forbearance versus 1.2 percent in non-majority-minority tracts. However, as a share of overall forbearances, loans in majority-minority tracts fell from 35.7 percent in March 2021 to 29.2 percent in January 2022 (an 18-percent decrease).

[6] The overall racial composition of the NMDB sample is White (75.7 percent), Black (6.6 percent), Hispanic (11.6 percent), and other race (6.0 percent).

Exhibit 2

Percentage of Borrowers in Forbearance by Majority-Minority Tract Status



Source: National Mortgage Database Program, Federal Housing Finance Agency and Consumer Financial Protection Bureau

Factors Related to Financial Capacity

Most borrowers who entered a COVID-19 forbearance have since exited.[7] An open question is when and how the borrowers who remain in forbearance will exit it. Understanding factors related to a household's financial capacity can shed light on this matter.

Following Durbin et al. (2021), the primary measures of financial capacity include pre-COVID-19 mortgage delinquency status, non-mortgage distress, single-borrower status, and relative income position (see appendix A). Prepandemic mortgage delinquency and non-mortgage distress serve as proxies for payment difficulty; single-borrower status and relative income position proxy for financial capacity.

Whether a borrower was delinquent on their mortgage immediately before the pandemic ("pre-COVID-19 delinquent") continues to be an important factor associated with a borrower's likelihood of having a loan in forbearance. Overall, pre-COVID-19 delinquency is strongly correlated with forbearance, as shown in exhibit 3. As of January 2022, the rate of forbearance among borrowers

[7] Publicly available estimates from Black Knight through January 2022 report that among borrowers who entered into a COVID-19 forbearance, 52 percent transitioned to performing status, 27 percent paid off their loan, 11 percent remained in active forbearance, 6 percent exited into post-forbearance loss mitigation, 3 percent were post-forbearance delinquent, and 1 percent were post-forbearance active foreclosure (Black Knight, Inc., 2022).

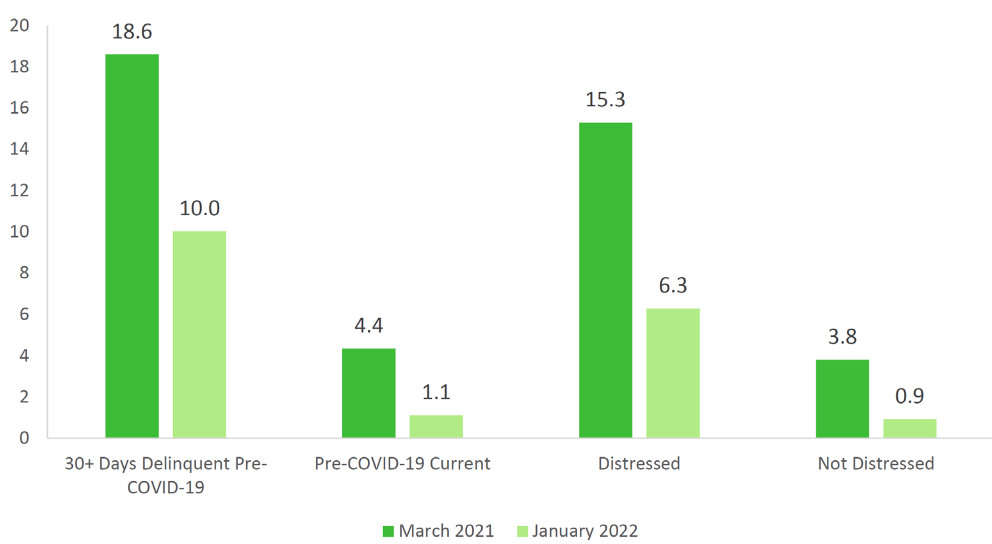
who were pre-COVID-19 delinquent was 10.0 percent. For the same period, only 1.1 percent of borrowers who were pre-COVID-19 current were in forbearance. Relative to March 2021, the pre-COVID-19 delinquent borrowers experienced a 46-percent decrease in forbearance rate, whereas the borrowers who were pre-COVID-19 current saw a 74-percent decrease.

However, pre-COVID-19 delinquency was also correlated with being delinquent and not in forbearance both in March 2021 and January 2022. The rate of 60+ day delinquency among borrowers who were pre-COVID-19 delinquent was roughly 15.4 percent in March 2021 and 3.7 percent in January 2022 (see appendix A). In contrast, the rate of delinquency for borrowers who were pre-COVID-19 current was 0.2 percent in March 2021 and 0.1 percent in January 2022.

Furthermore, comparing within groups, borrowers who were pre-COVID-19 current were significantly more likely to be in forbearance than to be delinquent compared with borrowers who were pre-COVID-19 delinquent. In January 2022, borrowers who were pre-COVID-19 current were 12.4 times more likely to be in forbearance than to be delinquent, whereas borrowers who were pre-COVID-19 delinquent were only 2.7 times as likely to be in forbearance than to be delinquent. Similar within-group patterns are observed in the March 2021 sample. Overall, the data suggest that pre-COVID-19 delinquent borrowers were less likely to have used COVID-19 forbearance protections to avoid delinquency compared with borrowers who were pre-COVID-19 current.

Exhibit 3

Percentage of Borrowers in Forbearance by Distress and Pre-COVID-19 Delinquency



Source: National Mortgage Database Program, Federal Housing Finance Agency and Consumer Financial Protection Bureau

A borrower is considered “distressed” if they were delinquent or in forbearance on an auto loan or credit card as of December 2021, the most recent data available. The share of January 2022 mortgage forbearances that belonged to distressed borrowers was 31.3 percent. This share is somewhat larger than the 25.4 percent reported in the March 2021 sample, which measured non-mortgage delinquency as of September 2020. Non-mortgage delinquency may be overestimated due to general seasonal delinquency in non-mortgage debt (for example, see Drukker and Nelson, 2018). Overall, the data show that distressed borrowers were 6.8 times more likely to be in forbearance than non-distressed borrowers in January 2022.

As shown in exhibit 4, single-borrower loans were about 1.6 times more likely to be in forbearance through January 2022 compared with loans with a co-borrower. This finding reveals an increase relative to March 2021, where single borrowers were only 1.4 times more likely to be in forbearance compared with co-borrowers. Furthermore, the share of forbearances that belonged to single borrowers increased to 64.7 percent in January 2022 from 59.6 percent in March 2021. Thus, forbearances remained relatively more common for loans with a single borrower than loans with multiple borrowers. This pattern could reflect that many single borrowers may be in single-income households and, thus, more resource constrained, on average, compared with dual-income households.

Exhibit 4

Percentage of Borrowers in Forbearance by Borrower Status

Source: National Mortgage Database Program, Federal Housing Finance Agency and Consumer Financial Protection Bureau

Living in a relatively lower-income tract is associated with a greater likelihood of forbearance, as shown in exhibit 5. In the January 2022 sample, borrowers in the lowest quartile of tract-to-MSA (metropolitan statistical area) income (Q1) were 1.7 times more likely to be in forbearance compared with borrowers in the highest quartile of tract-to-MSA income (Q4). Borrowers in the second (Q2) and third (Q3) quartiles of tract-to-MSA income were 1.4 and 1.2 times more likely to be in forbearance, respectively, compared with Q4 borrowers.

As a share of all forbearances, borrowers living in Q1 made up 33.7 percent of loans in forbearance, which is an increase relative to March 2021. It is also almost twice as large as the share of borrowers from Q4, which made up only 17.8 percent of loans in forbearance. On average, borrowers living in the lowest quartile of tract-to-MSA income would likely have fewer income resources compared with borrowers living in the highest quartile. Thus, borrowers in the lowest income quartile would have relatively less financial capacity.

Exhibit 5

Percentage of Borrowers in Forbearance by Quartile of Tract-to-MSA Income

Quartile of Tract-to-MSA Income	March 2021	January 2022
Income: Q1	5.5	1.6
Income: Q2	4.5	1.3
Income: Q3	4.2	1.2
Income: Q4	4.4	1.0

Source: National Mortgage Database Program, Federal Housing Finance Agency and Consumer Financial Protection Bureau

Overall, households with less financial capacity continue to be more likely to have loans in forbearance compared with those with relatively more financial capacity, on the basis of the measures presented in this analysis.

The Distribution of Current Loan-to-Value Ratios

Over the course of the pandemic, many homeowners experienced significant gains in home equity due to house price appreciation. One publicly available estimate is that house prices increased 26 percent over the 24-month period ending January 2022 (AEI, 2022). For borrowers who entered forbearance or were delinquent during or throughout the pandemic, house price appreciation would increase their home equity, all else equal. Unlike in past economic downturns in which house prices fell, significant house price appreciation may provide borrowers with additional opportunities to avoid foreclosure as CARES Act protections expire (for example, through rate-term refinancing, loan modification, or selling the home). The idea that borrowers can avoid foreclosure due to house price appreciation has been a topic of discussion throughout the pandemic (see Elul and Newton, 2021; Neal and Goodman, 2021).

To examine the evidence on the relationship between house price appreciation and LTV ratios, the authors report the distribution of current LTV ratios for three samples: March 2021, January 2022, and January 2022, restricted to loans open as of March 2021 or earlier (called the "restricted January 2022 sample"). By using the latter, changes can be isolated in the distribution of LTV ratios that come from loans that were open in March 2021, as opposed to the full January 2022 sample, which includes new mortgages (for example, for refinance or purchase) that originated between March 2021 and January 2022. The current LTV ratio is a mark-to-market measure based on house price index data from December 2021, the most recent data available.

Overall, the data show that few loans have high LTV ratios, as shown in exhibit 6. In the restricted January 2022 sample, loans with an LTV ratio above 95 percent accounted for 0.2 percent of the sample, and loans with an LTV ratio above 80 and up to 95 percent accounted for 6.2 percent of the sample. These findings reveal a decrease relative to March 2021, when the comparable numbers were 0.3 percent for an above-95-percent LTV ratio and 8.5 percent for an above-80 and up to 95-percent LTV ratio. Most loans in the sample had LTV ratios at or below 80 percent in January 2022. Furthermore, the share of loans with an LTV ratio between 60 and 80 percent increased significantly from 26.0 percent in March 2021 to 30.3 percent in the restricted January 2022 sample.

Similar patterns hold for the full January 2022 sample, with the share of all loans being slightly higher for LTV ratios above 60 percent. This finding is expected given that the sample includes new loans that often originate at LTV ratios of 80 percent or higher and may have benefited less from house price appreciation. Overall, the data suggest that house price appreciation increased the home equity of many borrowers during the pandemic.

Exhibit 6

Distribution of Loan-to-Value Ratio by Sample

LTV Group	March 2021	January 2022	January 2022 Restricted
<= 60.00	65.20	60.10	63.30
60.01–80.00	26.00	32.40	30.30
80.01–95.00	8.50	7.40	6.00
> 95.00	0.30	0.20	0.20

LTV = loan-to-value.
Notes: Numbers are percentages. Percentages may not add to 100 percent due to rounding.
Source: National Mortgage Database Program, Federal Housing Finance Agency and Consumer Financial Protection Bureau

Turning to the composition of loans in forbearance, between March 2021 and January 2022, the situation may have worsened for the relatively small number of borrowers with an LTV ratio above 95 percent, as shown in exhibit 7. Compared with borrowers with an LTV ratio greater than 80 and up to 95 percent, borrowers with an LTV ratio above 95 percent were 2.6 times more likely to be in forbearance and 8.5 times more likely to be 60+ days delinquent as of January 2022—a significant increase compared with the numbers for March 2021 (1.7 times more likely to be in forbearance and 7.4 times more likely to be 60+ days delinquent).

For borrowers with an LTV ratio above 95 percent, the 60+ day delinquency rate fell 48 percent between March 2021 and January 2022 (3.8 percent in January 2022 compared with 7.4 percent in March 2021), the smallest decrease for any LTV category considered. Borrowers with LTVs between 80 and 95 percent saw a 54-percent decrease, and borrowers with LTVs between 60 and 80 percent saw a 72-percent decrease between March 2021 and January 2022.

Exhibit 7

Percentage of Borrowers in Forbearance by Loan-to-Value Ratio

LTV Group	March 2021		January 2022	
	In Forbearance	60+ Days Delinquent	In Forbearance	60+ Days Delinquent
<= 60	3.5	0.4	0.8	0.1
60.01–80.00	5.9	0.6	1.6	0.2
80.01–95.00	8.9	1.0	3.4	0.5
> 95	15.3	7.4	8.6	3.8

LTV = loan-to-value.
Notes: Numbers are percentages. Percentages may not add to 100 percent due to rounding.
Source: National Mortgage Database Program, Federal Housing Finance Agency and Consumer Financial Protection Bureau

Overall, the data report that the level of home equity is related to a borrower's likelihood of having a mortgage loan that is in forbearance or delinquent. Specifically, borrowers with LTV ratios above 95 percent remain significantly more likely to have loans in forbearance or delinquent.

Conclusion

Most of the 8 million borrowers who entered mortgage forbearance due to the dire economic circumstances presented by the COVID-19 pandemic have exited. However, many borrowers remain in forbearance. This analysis provides insight into who these borrowers are. It also sheds light on the financial circumstances of these borrowers compared with borrowers who were in forbearance earlier in the pandemic.

As protections under the CARES Act have expired for many loans, what will happen to the borrowers who remain in forbearance is unclear. This analysis shows that these borrowers are more likely to be minorities and to live in majority-minority tracts. The data also show that these borrowers may have less financial capacity on certain dimensions, such as whether they were delinquent before the start of the pandemic. Although house price appreciation may provide additional opportunities for some of these borrowers, a small group of borrowers with little to no housing equity may be at a particularly high risk of foreclosure. Overall, the analysis suggests that borrowers remaining in forbearance may have relatively more difficulty avoiding foreclosure compared with borrowers who have already exited.

Variable Definitions

The following variables are used in this report and defined using data from the National Mortgage Database:

1. Race is defined on the basis of the primary borrower. *White* is non-Hispanic and White. *Black* is non-Hispanic and Black, including borrowers who reported two races, one being Black. *Hispanic* is based on reported ethnicity and can be for any race (White, Black, or other). *Other* includes non-Hispanic borrowers reported as American Indian, Asian, Native Hawaiian/Pacific Islander, or multiple races.

2. Current or mark-to-market LTV is estimated using information on the current first-lien loan balance and changes in the local home price index to estimate a current property value as of December 2021.

3. Single-borrower status is measured on the basis of whether the loan has only one borrower reported. If the loan reports more than one borrower, it is classified as a co-borrower loan.

4. Delinquency status in February 2020 is measured by the mortgage loan account status—specifically, whether the account is reported as 30+ days delinquent in February 2020, which is 1 month before the start of the COVID-19 pandemic.

5. Distress is measured at the household level on the basis of the borrower's performance on auto loans and credit cards, as reported through December 2021. A borrower is "distressed" if he or she is delinquent or in forbearance on an auto loan or credit card and "not distressed" if he or she has an auto loan or credit card but is not delinquent or in forbearance on either product. The focus is on auto loans and credit cards because, unlike with mortgages or student loans, forbearance is more likely to be discretionary because government-sponsored forbearance programs are not available for those products.

6. Relative income quartile is measured on the basis of the ratio of census tract-to-MSA income, which comes from the American Community Survey (ACS).

Appendix A

Exhibit A-1

Forbearance and 60+ Day Delinquency Rates by Borrower Characteristics, March 2021 and January 2022 (1 of 2)

Borrower Characteristic	March 2021		January 2022	
	In Forbearance	60+ Days Delinquent	In Forbearance	60+ Days Delinquent
White	3.67	0.50	1.08	0.14
Black	9.22	0.98	3.00	0.32
Hispanic	8.37	0.72	1.70	0.20
Other	5.58	0.26	0.92	0.08
LTV: <= 60.00	3.53	0.41	0.84	0.10
LTV: 60.01–80.00	5.93	0.64	1.56	0.18
LTV: 80.01–95.00	8.94	0.99	3.37	0.45
LTV: > 95.00	15.30	7.37	8.60	3.82
Single Borrower	5.39	0.73	1.52	0.21
Co-borrowers	3.87	0.35	0.98	0.08
Delinquent (30+ days) in Feb. 2020	18.60	15.40	10.03	3.66
Current in Feb. 2020	4.35	0.23	1.12	0.09
Distressed	15.30	3.39	6.29	1.28
Not Distressed	3.81	0.21	0.93	0.06

Exhibit A-1

Forbearance and 60+ Day Delinquency Rates by Borrower Characteristics, March 2021 and January 2022 (2 of 2)

Borrower Characteristic	March 2021		January 2022	
	In Forbearance	60+ Days Delinquent	In Forbearance	60+ Days Delinquent
Majority-Minority Tract	7.67	0.74	1.69	0.20
Not a Majority-Minority Tract	3.82	0.49	1.15	0.14
Income: Q1	5.50	0.80	1.61	0.23
Income: Q2	4.47	0.63	1.33	0.17
Income: Q3	4.23	0.45	1.17	0.13
Income: Q4	4.42	0.30	0.97	0.09

LTV = loan-to-value.
Notes: Numbers are percentages. Percentages may not add to 100 percent due to rounding.
Source: National Mortgage Database Program, Federal Housing Finance Agency and Consumer Financial Protection Bureau

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Heterogeneity in the Effect of COVID-19 Mortgage Forbearance: Evidence from Large Bank Servicers

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Abstract

This study examines the effectiveness of COVID-19 mortgage forbearance programs using data from the largest national bank servicers. Analyses of the data indicate that the forbearance entry rate was higher for borrowers with lower credit scores and in areas with higher unemployment rates. Some borrowers under forbearance had high credit scores, and a significant proportion continued to pay. Borrowers who had higher credit scores, made more payments under forbearance, and experienced greater labor market recovery were the earliest to exit the forbearance. Borrowers exited forbearance via different forms, with a large proportion delaying the payments of the forborne amount at maturity, refinance, or the property sale. One potential downside of nonpayment under forbearance is its adverse impact on ability to be refinanced, which is supported by some empirical evidence. However, the effect was short-lived, likely due to programs that attempted to alleviate this adverse effect. These pieces of evidence support an interpretation that forbearance programs supported borrowers adversely affected by COVID-19 event, but incentives should be built in to encourage exits to facilitate wealth accumulation.

Introduction

Mortgage forbearance programs in which borrowers can pause the monthly payment were a prominent and integral part of the broad relief programs enacted by Congress and government agencies, besides the accommodating fiscal and monetary policies, in response to the sharply rising unemployment rate caused by the containment measures during the COVID-19 pandemic.[1] With the benefit of hindsight, the housing market turned out to be robust and may have contributed to the broad economic recovery amid the arrival of vaccinations and the associated economic reopening by end of 2020.

Understanding the effects of COVID-19 mortgage forbearance programs, including borrowers' entry, payment behavior, exits, and post-exit performance, is crucial for several reasons.[2] For lenders or investors, understanding the borrower characteristics and behavior is instrumental to accurately forecast credit risk, set the right reserves, and make the appropriate credit provision decision. For servicers, understanding the characteristics of those who remain in the forbearance would help servicers offer targeted loss mitigation options. For policy makers, understanding the heterogeneity effect across the spectrum of borrower income, neighborhoods, etc., besides the overall effect on the mortgage and housing market, is critically important in evaluating the effect of such programs on wealth accumulation.

There is a burgeoning literature on the effect of COVID-19 forbearance programs (Farrell, Greig, and Zhao, 2020; Cherry et al., 2021), and this report makes a unique contribution by examining first-lien residential mortgage data from the largest 18 bank servicers.[3] Farrell, Greig, and Zhao (2020) use loan level mortgage data serviced by Chase Bank that is merged with the checking accounts of the borrower in the bank. Cherry et al. (2021) use credit bureau data and examine both mortgages and credit cards. The rich information from the bank servicers allows accurate identification of COVID-19 forbearance entry and exit as well as forms of exits. In addition, the data have unique features, including how banks manage the costs of servicing forborne Federal Housing Administration (FHA)/Veterans Administration (VA) loans.

This report uses FRB Y-14 data, which collect detailed loan- and borrower-level information from the largest depository mortgage servicers. As of December 2020, these data report close to 17 million mortgage loans totaling $3.4 trillion, approximately one-third of the U.S. mortgage market. Studies utilizing data on residential mortgages serviced by banks also help to better understand the behavior of banks amid sharply rising role of non-banks.[4]

[1] The Coronavirus Aid, Relief, and Economic Security Act (CARES Act), signed into law on March 27, 2020, created a forbearance program for federally backed mortgage loans and protected borrowers from negative credit reporting due to loan accommodations related to the COVID-19 national emergency declared by the President on March 13, 2020. On April 7, 2020, a revised inter-agency statement, in *OCC Bulletin* 2020-35, was issued to provide information to financial institutions that work with affected borrowers, including borrowers in non-federally backed residential mortgages. Note that although borrowers can suspend monthly payments without penalty (including the negative credit reporting) during the forbearance period, borrowers are expected to pay back the forborne amount eventually.

[2] Entry refers to mortgage borrowers' decision to sign up for the forbearance program; exit refers to the ending of the forbearance period. CARES Act prescribed eligibility periods for federally backed loans, while servicers can decide on the duration with renewal options for privately held residential mortgages.

[3] Other highly related articles include Agarwal et al. (2020) and Gerardi, Lambie-Hanson, and Willen (2021), which focus on heterogeneity across borrowers in refinance and wealth accumulation in the COVID-19 era. An et al. (2021) examine the borrower payment behavior by race and income during the COVID-19 pandemic. Capponi et al. (2021) investigate the effect of COVID-19 forbearance on refinance. Anderson, Harrison, and Seiler (2021) use an experimental design to examine strategic forbearance. Fuster et al. (2021) examine the credit supply in the U.S. mortgage market during the COVID-19 pandemic.

[4] Refer to Kim et al. (2018), Buchak et al. (2018), e.g., for studies on the rising role of nonbanks in the U.S. mortgage servicing and origination markets.

For macroeconomic variables, this study focuses on unemployment rates both nationally and locally. COVID-19 infection hotspots and the resulting containment measures, such as shelter-in-place, caused economic shocks. Although many people were able to work from home, others (particularly those in the travel, entertainment, and hospitality industries) were laid off or had work curtailed. The unemployment rate variable at county level from the Bureau of Labor Statistics helps capture the unemployment risk that a borrower faces.

Analyses of the data yielded the finding that forbearance entry was higher in areas with greater unemployment and for borrowers with lower credit scores. Analyses of the data indicated that a significant portion of borrowers under COVID-19 forbearance continued to pay. On forbearance exits, data analyses showed that the early exits from forbearance were borrowers with higher credit scores, and those facing improving employment conditions exited faster.

Empirical analyses yielded the finding that the entry sensitivity to unemployment shock was greater for higher credit-score borrowers and in neighborhoods with a greater percentage of higher-income households. Forbearance exit sensitivity to improving employment conditions was greater for lower credit-score borrowers. These pieces of evidence together are consistent with an interpretation that, although forbearance helped those adversely affected by the economic fallout from COVID-19, it also benefited borrowers with greater means to shoulder such shocks.[5]

Forbearance exits took many forms. Some borrowers reinstated and paid all forborne amounts before they exited. A large portion of them exited by deferring the forborne payments with two types: 1) deferring the forborne amount to a balloon payment until earlier of maturity, refinance, or the loan pay-off date; and 2) extending the contractual maturity to allow for missed payments to be collected. Some received modifications with rate change, term change, or both.

Most of the borrowers who exited the forbearance were current after the exits—they were able to make monthly payments after the exits, likely assisted by the COVID-19 deferral programs and the improving labor market. Their serious delinquency rate was higher, however, than that of the group that never went into COVID-19 forbearance, reflecting the additional risk factors of these borrowers. One group particularly contributed to the elevated serious delinquency rate of forbearance exits—borrowers who were late in payments before the entry into forbearance.

One potential downside of forbearance and the nonpayment it affords is that it might adversely affect the borrower's ability to refinance given the history of nonpayment (under forbearance). Evidence supporting this was found. However, government agencies, including government-sponsored enterprises (GSEs), put out programs to support refinance after borrowers exited. Analyses of data found evidence that the adverse effect of forbearance on refinance was short-lived.

It was also found that banks, for FHA/VA loans in Ginnie Mae (GNMA) securities, used buyouts to manage nonpaying FHA/VA loans under forbearance. Such nonpayment by borrowers meant that servicers needed to advance payment to investors. The data indicated that servicers bought out

[5] Evidence was found that borrowers who were late in payments before the COVID-19 pandemic joined forbearance, effectively obtaining a respite brought about by the forbearance program established in this pandemic.

such loans from GNMA securities and put them on their own book, avoiding the need to advance payments to investors in a declining interest rate environment.

The remainder of this report proceeds as follows. First, the data and the sample are presented. Then, forbearance entry decision is examined, followed by borrower payment behavior and exit decision and post-exit performance. After that, the effect of forbearance on refinance likelihood is examined, followed by an investigation of how servicers manage the cost of servicing FHA/VA loans via the buying out from GNMA pools. Concluding remarks end the report.

Data, Sample, and Variable Constructs

Data

This study uses FRB Y-14 (or Y-14) first lien mortgage loans reported monthly by the largest 18 bank servicers. Covering both the bank-held or serviced loans that are updated monthly with a lag of around 2–3 months, the Y-14 data contain a rich set of borrower- and loan-level variables both for origination and for loan performance including delinquency status, loss mitigations, and liquidations, etc.

Since the focus of the study is on the COVID-19 pandemic, the Y-14 data were utilized for the period from February 2020 until the most recent performance updates. To facilitate data analyses, a 10-percent random sample was constructed: a random 10 percent sample was selected for the snapshot of loans active as of February 2020, and their performances were followed; to incorporate originations after February 2020, a random 10 percent sample for originations in each following month was selected, and their performances at monthly frequency were tracked.[6]

Panel A of exhibit 1, in the right y-axis, shows that the number of active loans in the Y-14 data declined from 18.1 million in March 2020 to 16.2 million in December 2020; the visible decline in loan counts in Y-14 data reflect the significant number of refinancing, especially by nonbanks, amid the unprecedented low interest rates starting in March 2020.

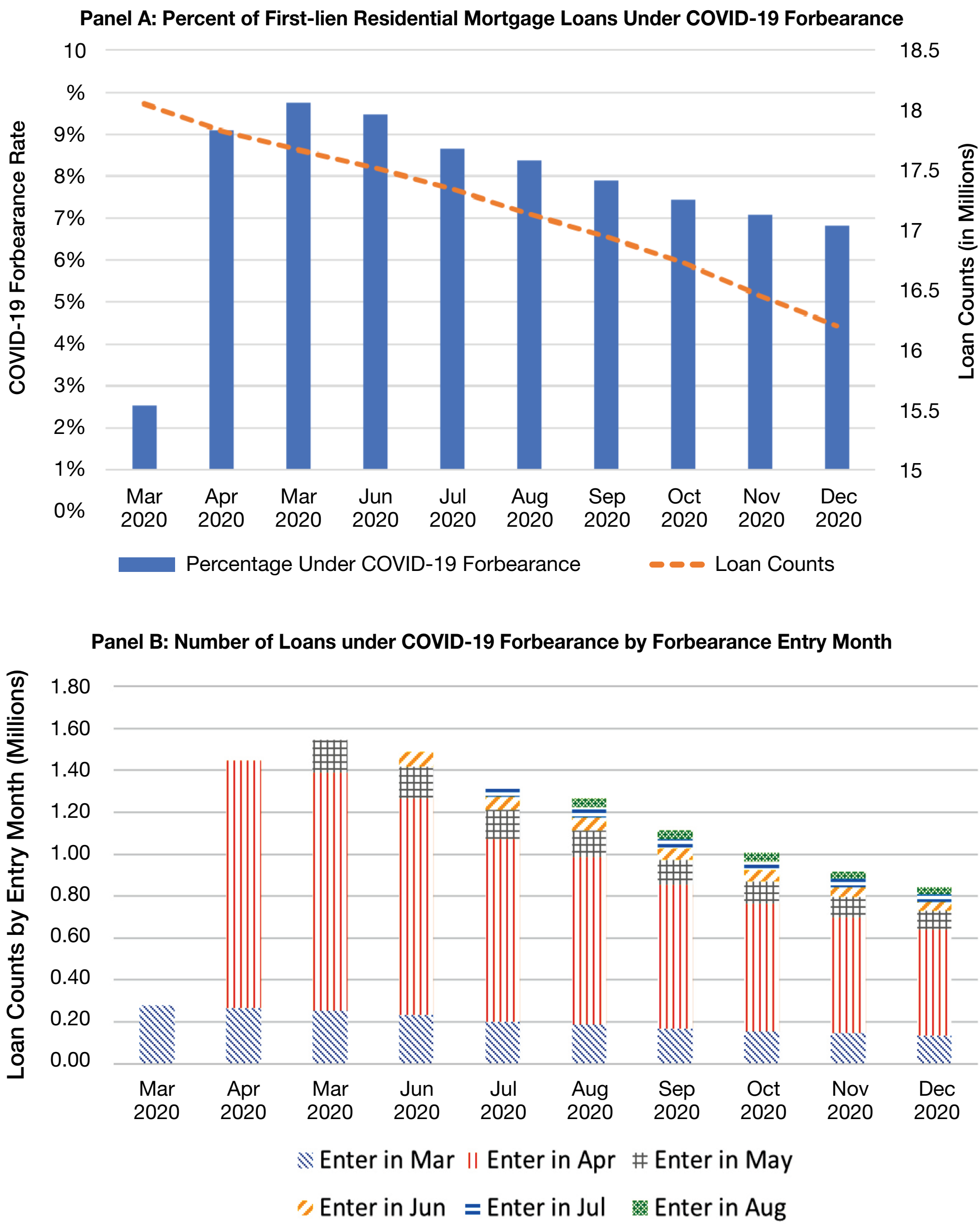
A key task was to identify the COVID-19 related forbearance. With the CARES Act enacted in March 2020, an interagency guidance was issued to servicers on the reporting of COVID-19 forbearance (and reporting of payment behavior while under forbearance to the credit bureaus). Servicers were instructed to record the COVID-19 forbearance under the variable "Loss_Mit_Performance_Status." However, because there were loans under loss mitigation prior to March 2020, such loans were not counted as COVID-19 forbearance.[7]

[6] Numbers reported in the exhibits are adjusted from the results taken directly from the random sample. For example, the loan counts reported in the exhibits are 10 times that of the loan counts of the random sample.

[7] The interagency Guidance did not specify whether loans under loss mitigation in March 2020 shall be treated as COVID-19 forbearance or not. The data indicated a reasonable jump in loans under loss mitigation in March. The baseline treatment was that such loans counted towards COVID-19 forbearance. The overall results changed little from an alternative treatment that these March 2020 loans did not count as COVID-19 forbearance.

Exhibit 1

Forbearance Rates and Numbers by Calendar Month



Sources: FRB Y-14 data with observation months from February 2020 to December 2020

Panel A of exhibit 1, in the left y-axis, shows the percent of first-lien residential mortgages under COVID-19 forbearance each month since March 2020. Consistent with the forbearance statistics from the Mortgage Banker Association, Black Knight, Inc., and Urban Institute, the percentage sharply jumped in April, peaked in May, and has since declined due to exits and fewer entries, as also shown in Panel B of exhibit 1, where loan counts under forbearance are plotted by entry month.

This pattern of forbearance applies to all investors and loan types. For the conventional first-lien mortgages serviced by the 18 largest bank servicers, the largest block, GSE, saw a significant decline in loans under forbearance (the peak number of 0.85 million in May 2020 declined to 0.42 million by December 2020), and so did conventional loans in private-label securitizations (or PLS) and bank-held portfolio as well as nonconventional loans with government mortgage insurance (FHA, VA, United States Department of Agriculture, etc.)

The total number of loans under forbearance, however, is the result of both forbearance entry and exits. To further understand and assess the impact of forbearance, forbearance entry and exit were examined, separately, under the next two subheadings.[8] The loan level data were also merged with various data sources to obtain macro-economic variables and geographic/demographic variations. For unemployment variables, the county-level unemployment rate variables from the Bureau of Labor Statistics (BLS) were utilized. For variables that capture zip-level percentage of higher income households, the 2019 American Community Survey dataset was used.

Sample and Variable Constructs for Forbearance Entry Analyses

Constructing the sample for examining entry into COVID-19 forbearance involved keeping all observations from the raw data except for removing observations after a loan enters the forbearance. The dependent variable, forbearance_entry, will take the value of 1 in the month a loan enters forbearance.

The CARES Act mandated that COVID-19 forbearance be readily available for federally backed residential mortgage loans, which include residential mortgage loans in GSE-guaranteed mortgage-backed securities (MBS) and FHA- or VA-insured mortgage loans typically packaged in GNMA MBS.[9] Bank-held loans or those in private label mortgage-backed securities (PLS) were not required by law to grant COVID-19 forbearance. Examining COVID-19 forbearance by investors was thus informative. Row 1 of exhibit 2 shows that GSE and portfolio loans had similar level of forbearance, whereas those for GNMA and PLS were higher. The forbearance entry rate for loans bought out from GNMA securities was particularly high; this is not surprising because servicers, by GNMA rules, typically buy out nonpaying loans, including nonpaying loans under COVID-19 forbearance that were contractually 90+ days past due (DPD).

[8] The COVID-19 forbearance entry analyses used data from February 2020 to December 2020. The analyses on COVID-19 forbearance exits and particularly loan performance after forbearance exits utilized the data with the latest monthly—July 2021—performance update.

[9] H.R.748 - CARES Act.

Exhibit 2

Summary Statistics of Sample for Forbearance Entry Analyses

Variable	Total (%)	GSE (%)	GNMA (%)	PLS (%)	Portfolio (%)	GNMA Buyout (%)
Under forbearance	1.1	0.9	1.8	2.2	1.0	4.8
Investor	100.0	64.0	14.2	2.8	16.1	0.7
FICO_Current Less than 579	3.6	1.7	6.9	16.0	3.0	48.9
580–619	2.5	1.3	5.7	9.1	2.0	13.5
620–679	7.0	4.9	14.7	17.1	5.6	14.6
680–719	9.1	8.0	14.4	13.3	7.4	5.0
720–759	13.9	13.7	16.5	13.6	13.1	2.7
760+	60.9	68.3	38.8	27.6	62.6	1.7
Missing	3.0	2.0	2.9	3.2	6.4	13.7
Refreshed LTV >=80	7.4	6.1	13.5	9.2	5.8	12.6
Debt to income less than 0.15	22.2	23.1	13.5	37.2	25.7	8.0
0.15–0.21	19.3	21.1	16.3	7.9	18.3	11.2
0.21–0.29	20.7	21.4	20.3	12.1	20.3	20.6
0.29–0.41	14.7	14.5	14.5	12.9	15.4	18.1
> 0.41	3.4	3.8	2.7	3.6	2.4	3.5
Missing	19.6	16.0	32.8	26.3	17.9	38.6
Loan type: Conventional w/o PMI	69.2	81.1	0.0	78.5	85.9	0.1
FHA	11.7	0.1	69.8	8.6	2.6	80.6
VA	3.7	0.0	23.7	1.3	0.5	12.9
Conventional w/ PMI	12.9	18.7	0.0	5.5	3.3	0.4
Loan Purpose: Purchase	41.2	35.8	63.2	43.0	39.9	74.5
Refi: rate	35.4	39.9	23.8	17.2	33.0	17.7
Refi: cash-out	19.0	20.0	7.3	37.3	22.7	6.8
Refi: home improvement	1.7	1.8	0.9	1.2	2.0	0.1
Loan Product: FRM 30 year	69.0	69.0	92.4	61.5	48.0	80.2
FRM 15 year	21.9	27.6	5.0	3.0	19.5	2.1
FRM 40 year	1.9	1.1	1.3	7.6	3.7	15.0
ARM	5.5	2.0	1.3	18.0	20.8	2.2
Occupancy: Primary Residence	89.2	87.5	96.8	85.3	89.0	98.9
Secondary home	4.1	4.7	0.1	2.6	6.0	0.1
Investment property	5.8	7.2	0.9	8.7	4.5	0.4
Loan Source: Retail	49.8	51.6	31.2	26.1	66.1	24.1
Broker	4.4	2.8	4.5	24.4	6.2	7.3
Correspondent	31.3	31.4	56.4	17.4	10.0	59.9
Interest Only: Yes	1.6	0.2	0.0	13.6	6.5	0.0
Balloon Payment: Yes	0.2	0.0	0.0	2.3	0.7	0.0
Documentation: Full	78.3	77.4	80.9	42.4	86.5	86.6
Negative Amortization: No	99.0	99.8	100.0	90.3	96.4	99.6
Prepayment Penalty: Yes	1.9	0.1	0.0	10.0	9.5	0.0
Unemployment rate	8.5	8.5	8.1	9.2	8.8	8.5
Pct_HHInc_abv_75k_zip	64.8	65.6	57.8	61.0	69.4	55.4

GSE = government sponsored enterprises. LTV = loan to value ratio. PLS = private-label securitizations. PMI = private mortgage insurance.
Note: Proportions may not sum to 100 percent as there are "other" categories.
Sources: 10 percent sample of FRB Y-14 data, Feb. 2020–Dec. 2020; Bureau of Labor Statistics; 2019 American Community Survey

In order to capture potentially nonlinear relationships between borrower credit scores and forbearance entry, borrower's current FICO scores were binned according to broadly accepted cutoff levels. More than 60 percent of loan-month observations were for borrowers with a FICO score greater than 760, suggesting that the largest national banks increasingly held on-book or serviced borrowers with pristine credit scores after the 2008 financial crisis.

In terms of investors, 64 percent of loan-month observations were for conventional loans in GSE, 14 percent in GNMA, 16 percent in portfolio, and 3 percent for PLS. In terms of loan type, around 81 percent of GSE loans were conventional loans without private mortgage insurance (or PMI). Close to 70 percent of GNMA loans were FHA. Close to 89 percent of bank-held loans were conventional loans, with 3 percent being FHA/VA. The majority of loans in early buyouts (EBO) were FHA/VA loans.

The share of borrowers with a current FICO score at or above 740 were highest for GSE and portfolio loans, much lower for GNMA and PLS loans, and were close to be 0 for EBO loans. Of particular interest is that the portion with current credit scored lower than 680 in EBO loans was close to one-half (more on EBO later in this report).[10]

The variation in the share of loans in refreshed loan-to-value ratio (LTV) above 80 percent is much less across investors. Across all investors, only 7.3 percent had a refreshed LTV greater than 80 percent, reflecting the recovering house market after the 2008 Great Financial Crisis and the robust housing market through the pandemic. Only 6 percent of GSE and portfolio loans were of LTV greater than 80 percent, as were 13 percent of GNMA and 11 percent of EBO loans. Variation across investor type on debt-to-income ratio (DTI) is large. For example, the share of missing DTI was 20 percent for all, 16 percent for GSE, 18 percent for portfolio, 33 percent for GNMA, and 39 percent for EBO loans.

Approximately 54 percent of loan-month observations were for refinance purpose; 41 percent were for purchase loans; GSE had the highest in refinance at 40 percent in rate or term refinance and 20 percent in cash-out refinance; and GNMA (and EBO) loans had a higher proportion of purchase loans, reflecting their mission of supporting first-time homebuyers. Close to 90 percent of all loans were fixed rate; portfolio loans had 21 percent in adjustable-rate loans, with PLS loans coming the second at 18 percent.

Three-fourths of the loans were for single-family detached residences, 8 percent for condos, 7 percent for townhouses, 3 percent for multifamily residential units (2- to 4-units), 5 percent for planned unit development, and 1 percent for manufactured homes. Close to 90 percent of loans were for primary residences, 4 percent were for second homes, and 6 percent were for investment properties.

Sources of loan origination vary across investor type. GSE loans had 52 percent originated via direct retail channel and 32 percent from correspondent channel. Bank-serviced GNMA loans sourced heavily from correspondent channels at 56 percent, with direct retail channels at 31 percent, suggesting a reliance on the correspondent channel for agency loans. For portfolio loans,

[10] Current FICO have missing values for two reasons: a borrower does not have a FICO score or borrowers may miss their current FICO in certain months. The majority of the cases in the data are the former.

two-thirds were originations via direct retail channel. PLS loans have a high percentage of broker originated loans, reflecting the prominent broker channel for loans originated prior to the 2008 financial crisis.

Ten percent of all loans have unpaid principal balance (UPB) greater than $379,000. However, the share was much larger, at 38 percent, for portfolio loans, reflecting that banks hold jumbo loans on their books. On the contrary, close to 90 percent of GNMA loans had a UPB lower than $231,000.

The seasoning of loans across investor type varies. Nearly 89 percent of PLS loans were originated more than 10 years ago, reflecting in general their originations prior to the 2008 financial crisis; portfolio loans had a higher percentage of less than 1 year of seasoning, reflecting that a newly originated loan typically stays on the bank's book for a few months before being sold to GSE or packaged into GNMA securities.

Interest only loans were only 2 percent of all loans; the rate was higher at 14 percent for PLS loans and 7 percent for portfolio loans. Loans with balloon payment features were close to zero, but the rate was 2.3 percent for PLS loans. Close to 78 percent of loans were full-documentation loans, with a lower level at 42 percent for PLS loans. Similarly, loans with negative amortization features were at 1 percent, but the rate was 10 percent for PLS loans and 4 percent for portfolio loans. The payment option ARM percent for all was 1 percent, but 9 percent for PLS and 3 percent for portfolio loans. Lastly, 2 percent of all loans had prepayment penalty clauses, but 10 percent of PLS and 9.5 percent of portfolio loans had such clauses.

On community-level variables, the number of mortgage borrowers having distinct levels of household income from the 2019 American Community Survey (ACS) were used to construct a variable measuring the percentage of households having annual income greater than $75,000. This variable was constructed at the ZIP Code level. Across the 31,623 ZIP Codes, the mean was 52 percent (the median is 53 percent). That is, in an average ZIP Code, 52 percent of households carrying a mortgage had an annual income above $75,000 in 2019. These data were then merged with the main analyses sample at ZIP Code-level with 99.8 percent of loan-month observations being matched.

The resulting data show that an average loan in the final data was in a ZIP Code where 65 percent of households had an annual income greater than $75,000 in 2019. An average GNMA loan was in a ZIP Code where 58 percent of households had an annual income greater than $75,000; an average portfolio loan was in a ZIP Code with 69 percent having an annual household income greater than $75,000.

The unemployment data were sourced from U.S. Department of Labor; the most granular were at the county level. The mean unemployment rate (weighted by labor force) across February 2020 to December 2020 was 8.4 percent. This county-month level data were then merged with the loan-level sample, which had a ZIP Code identifier, using the ZIP-county crosswalk file available through HUD. Shown in the last row of exhibit 2, the mean unemployment rate across all loan-months was 8.5 percent.

Sample and Variable Constructs for Forbearance Exit Analyses

Constructing the data to examine exit from COVID-19 forbearance entails keeping the loan-month observations for those who ever entered COVID-19 forbearance for the months after they entered forbearance. The dependent variable, forbearance_exit, takes the value of 1 in the months when and after a borrower exited the forbearance.

The pattern of the borrower- and loan-level characteristics for the exit sample is distinct from that for the forbearance entry analyses sample. For example, in the exit analyses sample, 41 percent of GSE loans and 38 percent of borrowers had current FICO scores greater than 760, while those numbers were 68 percent and 63 percent, respectively, in the entry analyses sample (reflecting the overall sample to a large degree). This suggests that disproportionately more borrowers with lower FICO scores entered the forbearance; it also shows that even borrowers with high FICO scores entered forbearance. The following section investigates this in more depth.

Forbearance Entry

Bivariate analyses were conducted on relationships between COVID-19 forbearance entry and contributing factors, followed by multivariate regression analyses.

Bi-Variate Analyses

How COVID-19 forbearance entry responded to sharply rising unemployment rates was examined first, followed by an investigation of how the pattern varied across borrowers by credit scores.

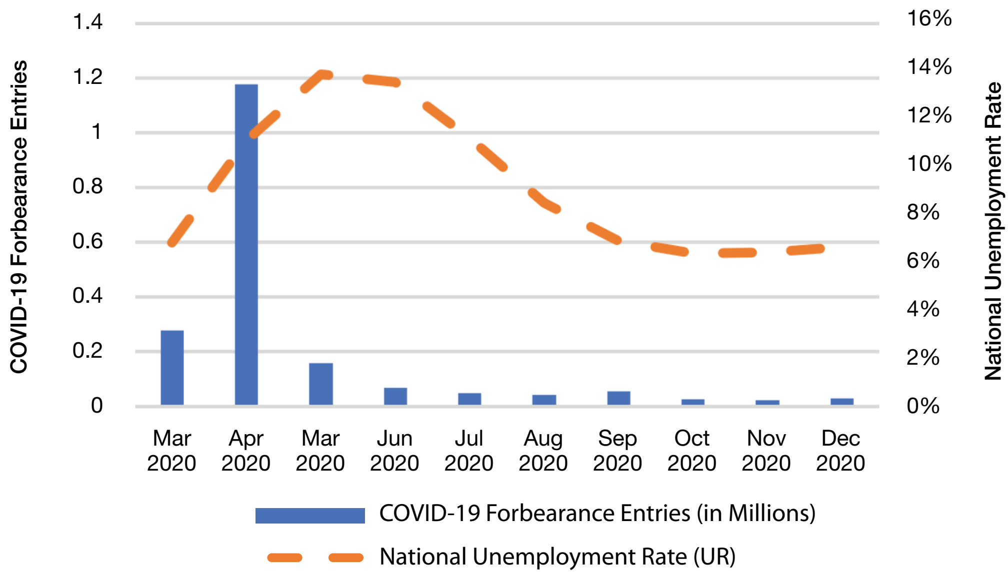
A. Forbearance Entry and Unemployment Shock

The time-series correlation between the national forbearance rate and the national unemployment rate was examined first. Panel A of exhibit 3 shows that the increase in forbearance entry directly coincided with the increase in unemployment: The largest forbearance entry was in April 2020—1.2 million borrowers entered forbearance in April, and 0.2 million entered in May, whereas the national unemployment rate climbed from 6.9 percent in March to 11.1 percent in April and 13.9 percent in May before it started subsiding in June 2020.

Exhibit 3

Forbearance Entry by Unemployment Rate and Borrower FICO (1 of 2)

Panel A: COVID-19 Forbearance Entries and Unemployment Rate - Over Time Relation



Panel B: COVID-19 Forbearance Entry Rate and Unemployment Rate (UR) Percentiles

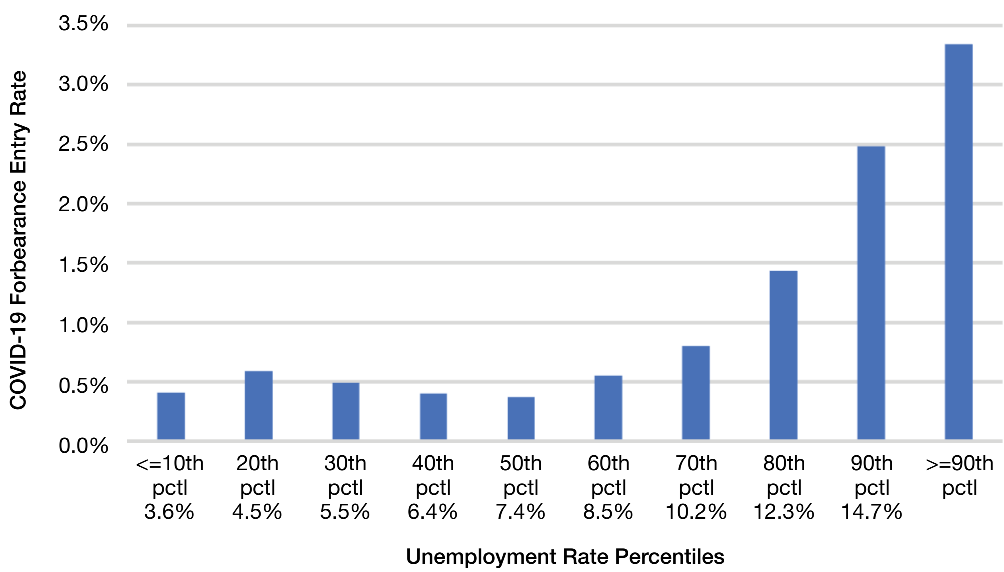
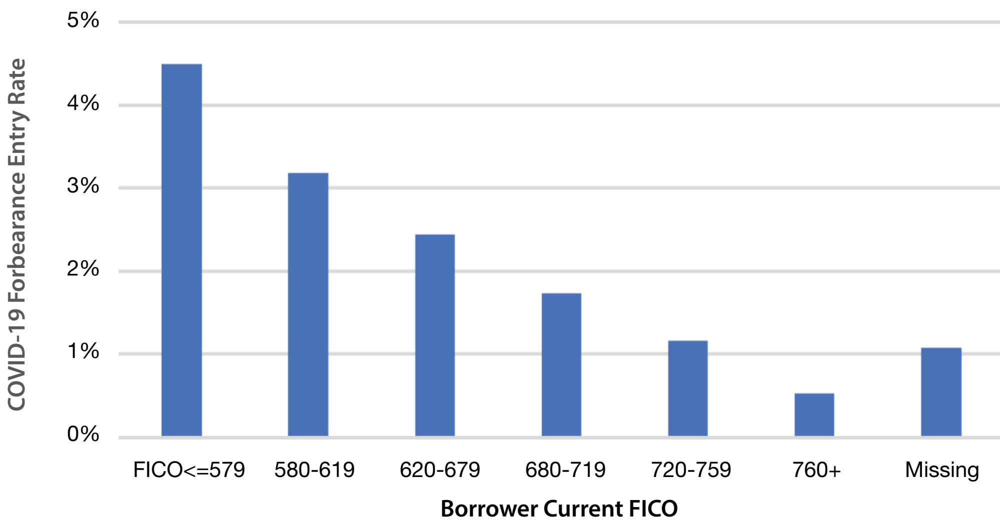


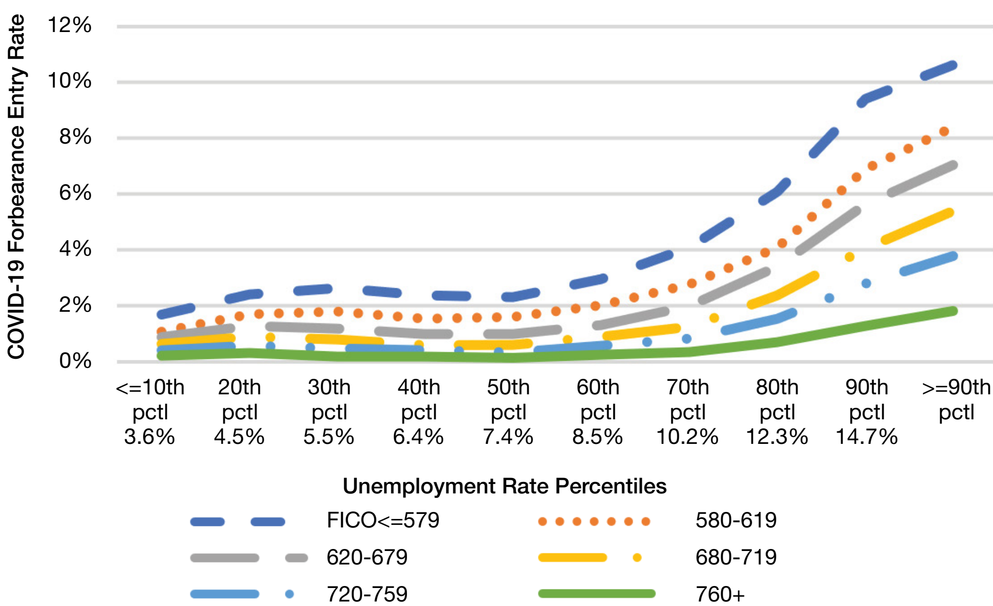
Exhibit 3

Forbearance Entry by Unemployment Rate and Borrower FICO (2 of 2)

Panel C: COVID-19 Forbearance Entry Rate and Borrower Current FICO



Panel D: COVID-19 Forbearance Entry Rate and Unemployment Rate Percentiles, by FICO Bands



Sources: FRB Y-14 data with observation months from February 2020 to December 2020; Bureau of Labor Statistics

Panel B of exhibit 3 plots the forbearance entry rate by the deciles of the unemployment rate variable. That is, all loan-month observations were pooled, and 10 deciles were created by the level of the unemployment rate variable. Therefore, the variation across the deciles included both the time-series and the cross-sectional (across county/ZIP) variation. For county-months that experienced unemployment rates ranging from fifth decile (or 50th percentile) of 7.4 percent to the ninth decile (or 90th percentile) of 14.7 percent or higher, the forbearance entry rate increased significantly with the unemployment rate. The forbearance entry rate for those areas with lower levels of unemployment rate was relatively flat.

B. Forbearance Entry and Borrower Credit Score

Panel C of exhibit 3 plots the forbearance entry rate as a function of the borrower's current FICO score. Borrowers with lower refreshed FICO scores entered forbearance significantly more often than those with higher scores; for example, borrowers with FICO scores lower than 579 have a forbearance entry rate that is 9 times of that of borrowers with FICO scores greater than 760.[11]

C. Forbearance-Unemployment Sensitivity as a Function of FICO

Of particular interest is the heterogeneity in borrowers' forbearance entry response to the unemployment shock. Is it stronger for borrowers with lower credit scores because they likely benefit more from the payment respite provided by the forbearance? Panel D of exhibit 3 offers a visual inspection of this relationship. These data confirm that borrowers with lower credit scores utilized the forbearance more. These data also confirm that the entry rate was higher when unemployment rate was higher.

Panel D of exhibit 3 also shows that while lower FICO borrowers utilized forbearance more in response to higher unemployment rates, the relative responsiveness was slightly greater for higher-scoring FICO borrowers. For example, for borrowers with the lowest credit score, the forbearance rate changed from 1.7 percent to 10.6 percent, an increase of 5.4 fold when the unemployment rate moved from lower than 3.6 percent to greater than 14.7 percent, and the forbearance rate for the highest-scoring FICO group was from 0.2 percent to 1.8 percent, an increase of 7.3 fold.[12]

Econometric Regression Analyses

While the bivariate relationships between forbearance entry and borrower credit scores as well as unemployment rates are presented, the relationship abstracts from the difference in many other borrower and loan characteristics. Regression analyses were thus conducted where these characteristics were included. Summary statistics of these variables are presented in exhibit 2.

The following equation was estimated to examine factors that affect COVID-19 forbearance entry:

$$Ln\left(\frac{p_{ict}}{1-p_{ict}}\right) = \beta_x X_{i,t} + \beta_u UR_{c,t} + \gamma UR_{c,t} * X_{i,t} + \alpha_s + \alpha_{sv} + \varepsilon_{ict} \qquad (1)$$

[11] Not reported in tables or figures, the pattern slightly changes for FHA borrowers, mainly for the lowest FICO bands, reflecting the heterogeneity in forbearance entry by loan type (and various dimensions).

[12] Another dimension not present in the exhibits is the borrowers who were already delinquent prior to their entry to COVID-19 forbearance. Comparing noncurrent ones that entered forbearance with current ones that entered yielded the finding that the formers' FICO was approximately 100 points lower than the latter group's.

where

p=probability (*Enter*=1) where Enter changes from 0 to 1 when a borrower enters COVID-19 forbearance;

i is loan; *c* is county; *t* is month;

X: borrower-, loan-, or community-level characteristics as detailed in exhibit 2;

UR: county-level unemployment rate (merged to zip-level in Y-14);

s: state; *sv*: servicer

State and servicer fixed effects are included in the baseline specification to capture time invariant state- and servicer-level heterogeneity in forbearance practices. Since the dependent variable is an indicator variable, the equation was estimated using a logistic regression—the dependent variable in the regression is the log of odds of entering COVID-19 forbearance.

Panel A of exhibit 4 presents the estimation results on forbearance entry using the full sample. Column 1 shows the result from the baseline specification, columns 2 and 3 add the unemployment variable interacting with the borrower FICO and community-level variable, respectively. Each specification shows the coefficient estimate and the robust standard error (StdErr).

Exhibit 4

Regressions on COVID-19 Forbearance Entry (1 of 2)

Panel A: Full Sample—All Investors

Variable	Class	(1) Estimate	StdErr	(2) Estimate	StdErr	(3) Estimate	StdErr
Intercept		– 4.72***	0.19	– 4.68***	0.19	– 4.63***	0.20
FICO_Current (lag)	580–619	0.53***	0.01	0.65***	0.02	0.53***	0.01
(omitted group: <580)	620–679	0.40***	0.01	0.39***	0.01	0.40***	0.01
	680–719	0.10***	0.01	– 0.01	0.01	0.10***	0.01
	720–759	– 0.26***	0.01	– 0.43***	0.01	– 0.26***	0.01
	760+	– 0.97***	0.01	– 1.18***	0.01	– 0.98***	0.01
	Missing	– 0.40***	0.01	– 0.28***	0.03	– 0.40***	0.01
Unemployment Rate (UR)		0.15***	0.00	0.14***	0.00	0.12***	0.00
UR*FICO_Curr (lag)	580–619			– 0.01***	0.00		
	620–679			0.00	0.00		
	680–719			0.01***	0.00		
	720–759			0.01***	0.00		
	760+			0.02***	0.00		
	Missing			– 0.01***	0.00		
Pct_abv_75k (zip)						– 0.19***	0.04
UR*pct_abv_75k						0.06***	0.00
Servicer, State fixed effects		Yes		Yes		Yes	
AUC		0.814		0.815		0.81	
Observations				17.7 Million			

Exhibit 4

Regressions on COVID-19 Forbearance Entry (2 of 2)

Panel B: Sub-Sample Analyses of COVID-19 Forbearance Entry—by Investors									
		GSA		FHA/VA		Portfolio		PLS	
Variable	Class	Estimate	StdErr	Estimate	StdErr	Estimate	StdErr	Estimate	StdErr
Intercept		– 4.36***	1.09	– 6.96	59.09	– 6.29	41.05	– 32.83**	14.13
FICO_Current (lag)	580–619	0.78***	0.03	0.61***	0.03	0.52***	0.06	0.30***	0.07
(omitted: <580)	620–679	0.46***	0.02	0.34***	0.02	0.29***	0.04	0.17***	0.05
	680–719	0.06***	0.02	– 0.14***	0.03	0.13***	0.04	– 0.01	0.06
	720–759	– 0.38***	0.02	– 0.51***	0.03	– 0.36***	0.04	– 0.36***	0.07
	760+	– 1.15***	0.02	– 1.23***	0.03	– 1.06***	0.03	– 0.78***	0.06
	Missing	– 0.61***	0.05	– 0.01	0.04	– 0.28***	0.07	0.08	0.12
Unemployment Rate (UR)		0.15***	0.00	0.14***	0.00	0.14	0.00	0.15***	0.00
UR*FICO_Curr (lag)	580–619	– 0.02***	0.00	– 0.01***	0.00	– 0.01***	0.00	0.00	0.00
	620–679	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.00
	680–719	0.01***	0.00	0.01***	0.00	0.00***	0.00	0.01***	0.00
	720–759	0.01***	0.00	0.01***	0.00	0.02***	0.00	0.02***	0.00
	760+	0.02***	0.00	0.02***	0.00	0.01***	0.00	0.02***	0.00
Servicer, State FE		Yes		Yes		Yes		Yes	
AUC		0.812		0.794		0.82		0.77	
Observations		10.1M		2.40M		2.45M		0.44M	

AUC = Area under the ROC curve. GSE = government sponsored entities. FE = fixed effects. FHA = Federal Housing Administration. VA = Veterans Administration. PLS = private-label securitizations.

** = statistically significant at 10 percent level. ** = statistically significant at 5 percent level. *** = statistically significant at 1 percent level.*

Note: Borrower/loan attributes have been included.

Source: 10 percent sample of FRB Y-14, February 2020–December 2020

Across the three specifications in Panel A, borrowers with greater credit scores utilize forbearance less. For example, borrowers with FICO scores greater than 760 (lagged 1 month), controlling for the explanatory variables, have a log-odds ratio of entering forbearance that is 0.97 lower than those with scores lower than 579 (the omitted group). This relationship is consistent with an interpretation that borrowers with greater scores had a less need for payment forbearance in face of pandemic-induced economic disruption.[13]

The unemployment shock unleashed by the response to the pandemic has a large impact on borrowers' forbearance entry. The estimated coefficient on the unemployment rate variable (in percent), 0.15, suggests that moving from a 25th percentile level of 5.0 percent to a 75th percentile of 11.2 percent is associated with an increase in log-odds of forbearance entry of 0.15*6.2 = 0.93,

[13] Shown in exhibit 4 is also the finding that borrowers with missing FICO have a lower COVID-19 forbearance entry rate (relative to borrowers with the lowest FICO scores). Shown in later exhibits, once entering COVID-19 forbearance, this group had lower exit rates and higher serious delinquency rates (relative to borrowers with FICO lower than 680). This is likely because these borrowers had a lower likelihood to apply for the COVID-19 forbearance or had a lower response rate to servicers.

a level comparable to the log-odds difference between borrowers with credit scores below 579 versus above 760.[14]

Other explanatory variables are of expected signs (estimated coefficients are reported in appendix exhibit A1). Borrowers with greater LTV ratios utilize forbearance more, but the impact of the LTV variable is of lower magnitude than that of FICO variation. Borrowers with greater debt-to-income ratios utilize forbearance more, reflecting a potentially greater need for support in case of an unemployment shock. The investor of the loan turns out to have little impact on forbearance utilization, possibly because other borrower and loan characteristics capture the key variations and because servicers offered forbearance to privately held loans as well. Compared with conventional loans, FHA loans have higher forbearance rates, consistent with their greater need for forbearance support due to the generally lower income of FHA loan borrowers.

Estimated coefficients in exhibit A1 also indicate that mortgages for investment purpose have higher forbearance rates than those for primary residences, and broker-originated mortgages are associated with a greater forbearance rate. Compared with 30-year terms, those having 15-year terms had lower forbearance rates. Loans with low- or no-documentation had higher forbearance rates than full-doc loans, and so did mortgages with negative amortization product features.

Do borrowers already late in payments utilize forbearance? According to the CARES Act, as long as borrowers experience hardship due to the pandemic, they can qualify. Therefore, a borrower already late in payment could utilize this support; indeed exhibit A1 shows that borrowers with a delinquency in past months have a greater likelihood of entering forbearance.

Column 2 of Panel A reports regression results on how borrowers' forbearance responses to unemployment shock vary with borrower characteristics using an econometric specification interacting the unemployment variable with the FICO category variables. The finding is that the compared with borrowers with FICO scores lower than 580, those with scores 680–719, 720–760, and especially above 760 have additional forbearance responsiveness to unemployment—the log-odds of forbearance entry response to unemployment for those with FICO 760+ is higher by an additional 0.02 on a base of 0.17. This regression result thus resonates with the visual presentation in Panel D of exhibit 3.

These results from this forbearance entry analysis are consistent with an interpretation that while forbearance supported borrowers with the highest vulnerability, it also provided borrowers from the full credit score spectrum a means to weather the economic shock resulting from the pandemic, and borrowers with higher credit scores disproportionately utilized it.[15] However, this result could be unique to these data, and it would be illuminative to see whether this holds for the broader mortgage market, including those serviced by non-banks.

[14] Not shown are results using the unemployment rate lagged by 1 month. The negative coefficient suggests that it is not what transpired in the labor market, but rather what has been transpiring that propels borrowers into forbearance. This evidence is thus consistent with interpretations that forbearance supported borrowers hit by unemployment, but it also provided a means to take precautionary action.

[15] The sample focusing on the period up to May 2020, when the forbearance entry was the most prominent, was also examined; the same pattern was found.

Communities vary in the proportion of mortgage holders whose household income is greater than $75,000. ZIP Code-level variables and their interaction with the unemployment rate variables were thus included in the estimated equation. Not surprisingly, the finding is that the coefficient on the variable is negative; that is, mortgagees in higher-income ZIP Codes utilize forbearance less. The coefficient on the interaction term is positive, implying that the forbearance entry response to unemployment shock in wealthier communities is greater than those in less wealthy ones.

Sub-Sample Forbearance Entry Regression Analyses

Panel B of exhibit 4 presents results from sub-sample regression analyses of forbearance entry. GSE loans, FHA/VA loans, portfolio loans, and loans in PLS were examined separately.[16] The focus was on the specification with unemployment and borrower credit score interaction. Across the sub-samples, the finding is that borrowers with greater credit scores have a lower likelihood of entering forbearance. In addition, the borrowers with greater credit scores are more responsive in their forbearance entry in face of the unemployment shock across the sub-samples.

Partly for brevity, coefficients on servicer fixed effects are not reported. The finding is that the coefficients on servicer fixed effects are statistically insignificant for bank-serviced loans in GSE securities, insured by FHA/VA, or in PLS, but they are significant for loans held in banks' portfolios. This reflects that 1) CARES Act mandated COVID-19 forbearance for federally backed loans, and GSE and HUD issued explicit guidelines for servicers to follow; 2) banks have greater discretion in providing relief programs to borrowers in loans held on their books; and 3) there are greater challenges and heterogeneity (including qualification requirements as well as duration of the forbearance and repayment options) in providing relief to mortgages in private label securities (Kaul, 2020).

Payment Under Forbearance, Forbearance Exit, and Performance Post Exit

Sample

In this section the focus is on the forbearance entrants' payment behavior, their exits, and performance after exits; therefore, the sample of analyses for this section are only borrower-month observations after the forbearance entrance month. The number of borrower-month observations as of December 2020 in the 10 percent sample is 1,532,116, reflecting the 1.9 million forbearance entrants since March 2020, with the reporting month ending December 2020. Approximately 1.0 million entrants have ever exited forbearance as of December 2020. A small portion, around 0.05 million, exited but re-entered forbearance. As of December 2020, 0.95 million, or 5.8 percent of active borrowers, remained under forbearance.[17]

[16] This is not an exactly mutually exclusive way of dividing investors; however, this way helps highlight the party who ultimately bears the (credit) risk.

[17] These numbers are very closely in line with what is reported by external vendors (given that banks serviced close to one-third of the U.S. market). For example, https://occ.bulletinintelligence.com/briefing?d=2021-01-07&doctypecode=occ reports that an estimated 2.7 million borrowers remained under forbearance then.

In constructing the sample for loan performance analyses after forbearance exits, loan-month observations after forbearance-exit month were used, and their loan performances were compared with the overall sample using all loan-month observations.

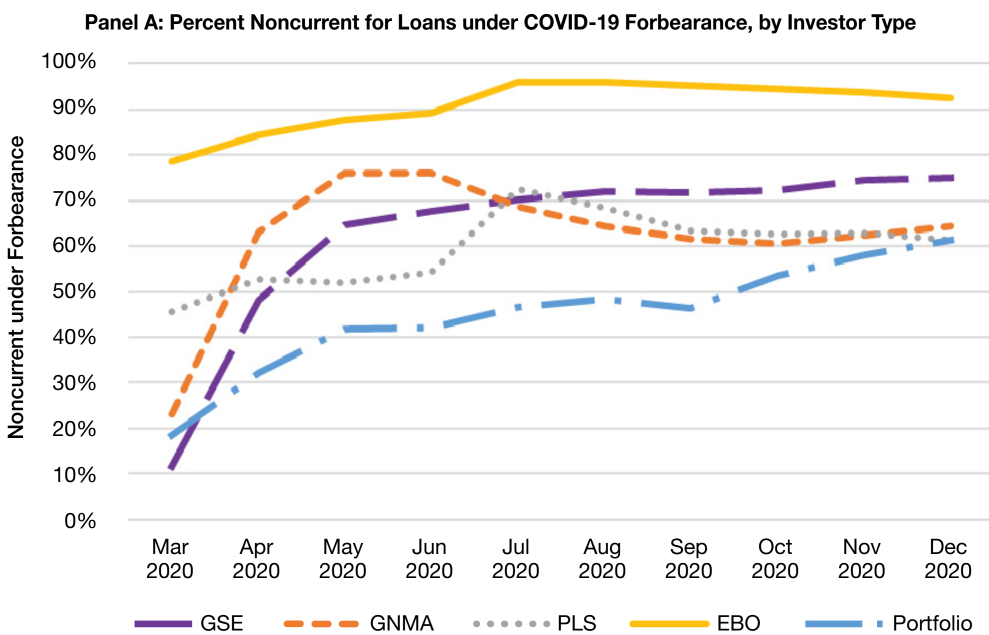
Borrower Payment Behavior under Forbearance

The goal of the forbearance program is to pause monthly payments and allow borrowers a respite before they can regain economic footing and resume payment. Nonpayment is thus expected; CARES Act mandates that nonpayment under COVID-19 forbearance shall not be reported as further delinquency to the credit bureau. Servicing platform data, such as Y-14 data, track contractual delinquency and is different from data reported to the credit bureaus.

Panel A of exhibit 5 shows the nonpayment rate by investor type over time.[18] EBO loans had the highest nonpayment rate; the high nonpayment rate was probably a main driver for doing the buyouts by the servicer in the first place. GSE loans had a nonpayment rate of 62 percent in May 2020, implying that 38 percent of those under forbearance still were paying. The nonpayment rate declined to 32 percent in December 2020. Portfolio loans consistently had the lowest nonpayment rate over time; for example, close to 60 percent of those in forbearance paid in May 2020. The increase in nonpaying rate over time was true across investor types, likely reflecting the exits of those with greater ability to pay and the stay of borrowers with a lower ability (or willingness) to pay.

Exhibit 5

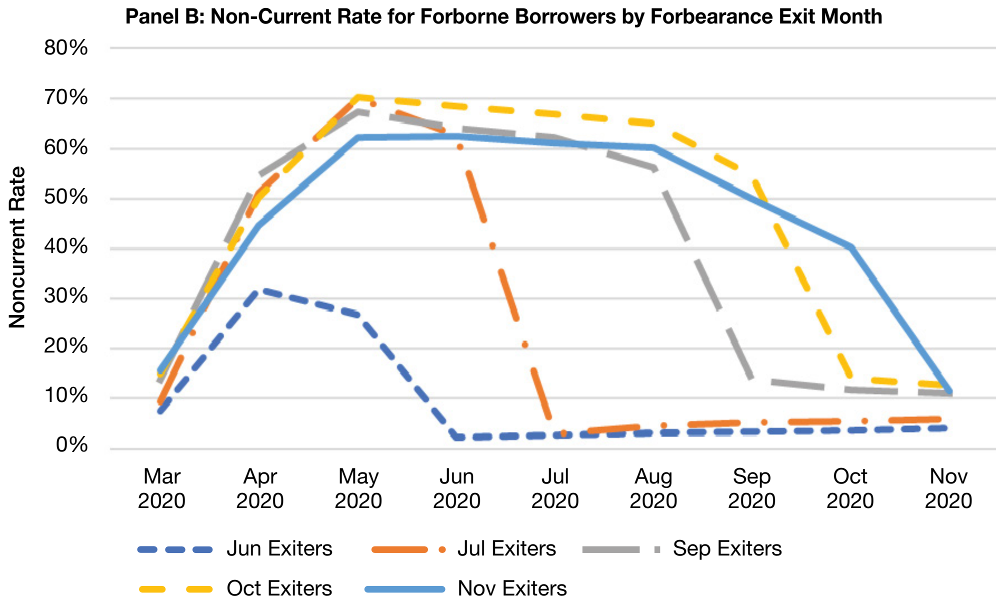
Borrowers' Payment Behavior under COVID-19 Forbearance (1 of 2)



[18] In this subsection on payment behavior under forbearance, the nonpayment is used interchangeably with non-current.

Exhibit 5

Borrowers' Payment Behavior under COVID-19 Forbearance (2 of 2)



EBO = early buyout. GNMA = Ginnie Mae. GSE = government sponsored entities. PLS = private-label securitizations.

Notes: Non-current includes nonpayment under forbearance. EBO are loans bought out of GNMA securities pools. Jun exiters refer to forborne borrowers who exited COVID-19 forbearance in June 2020, and so on.

Source: FRB Y-14 data with observation months from February 2020 to December 2020

The nonpaying behavior for borrowers under forbearance could be due to the borrowers' inability to pay due to the unemployment shock; it could also be due to borrowers' strategic choices to not pay in order to accumulate liquidity for future potential income or unemployment shocks. Panel B of exhibit 5 plots the nonpayment rate per month following borrowers who exited in different months. For example, for borrowers who exited forbearance in July 2020, the nonpaying rate was consistently high until June 2020 before it dropped in July, when the borrowers exited the forbearance, and it remained low afterwards. This pattern persists for exits in different exit months (the earlier exits overall had a lower noncurrent rate post-exits). It appears that once borrowers exit the forbearance, their payment behavior distinctly changes. In the sections below the focus is therefore on borrower forbearance exits and their performance post-exit.

Exiting Forbearance

Summary Statistics

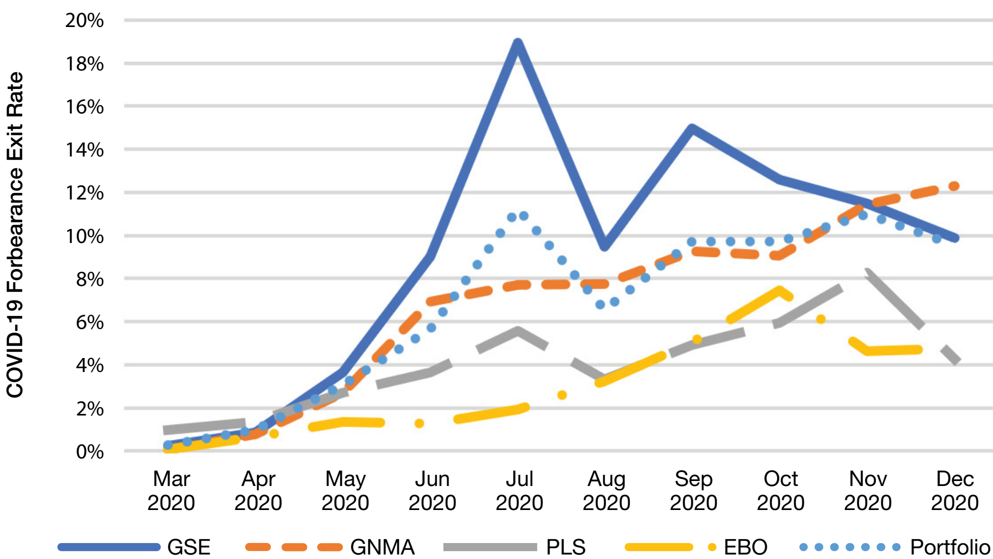
A glimpse of the forbearance exits can be caught from Panel B of exhibit 1, which plots the number of loan remaining under forbearance by entry month. For example, 1.2 million loans entered forbearance in April, and by the last reporting month, 0.5 million remained for these April entrants, i.e., 0.7 million of the April entrants exited by December 2020. The pattern is similar for loans entering forbearance in later months.[19]

Panel A of exhibit 6 offers an explicit examination of forbearance exit rates over time and by investor type. The y-axis is the percent of the current number of borrowers under forbearance that exits in the month. GSE loans had the highest exit rate, particularly in July 2020, likely reflecting the 3-month mark for the April entrants. Portfolio loans also had a relatively high exit rate in July 2020. The second highest exit rate for GSE loans was in September 2020, after which the exit rate declined. Portfolio loans, while having overall lower exit rates than GSE loans, had more stable exit rates since July 2020. GNMA loans had similar levels of exit rates than portfolio loans, but this was because of the early buyouts by servicers. EBO loans had consistently low forbearance exit rates, similar to the level for loans in private label securities.

Exhibit 6

Forbearance Exit by Unemployment Rate and Borrower FICO (1 of 3)

Panel A: COVID-19 Forbearance Exit Rate by Investor Type

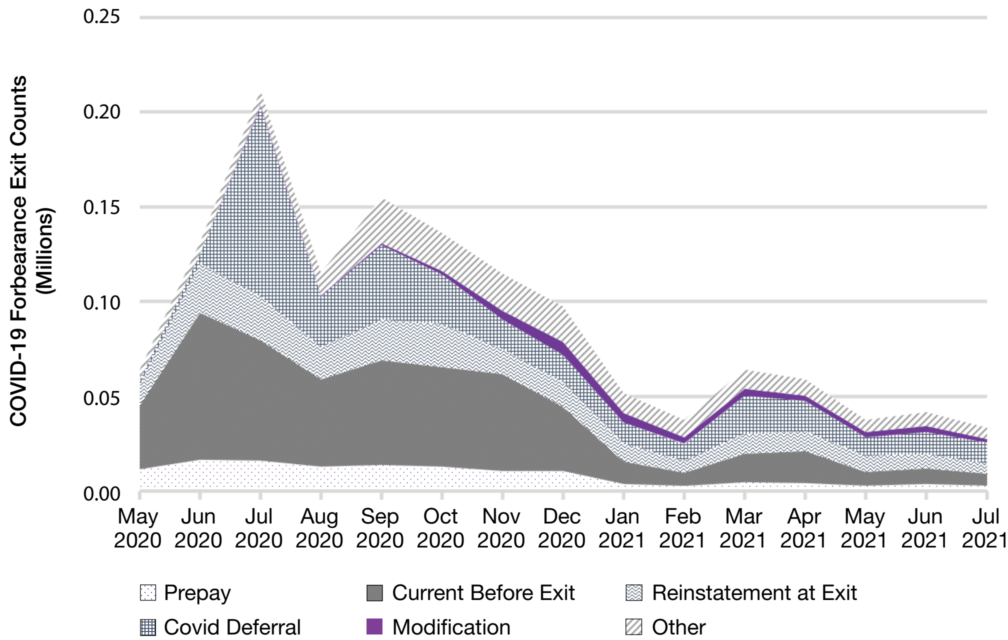


[19] Timing of exits was partially due to servicers' designs of forbearance programs; servicer fixed effects were thus included in the regression analyses. Analyses were conducted by investor type as applicable.

Exhibit 6

Forbearance Exit by Unemployment Rate and Borrower FICO (2 of 3)

Panel B: COVID-19 Forbearance Exit Counts by Exit Type



Panel C: COVID-19 Forbearance Exit Rate by Borrower FICO

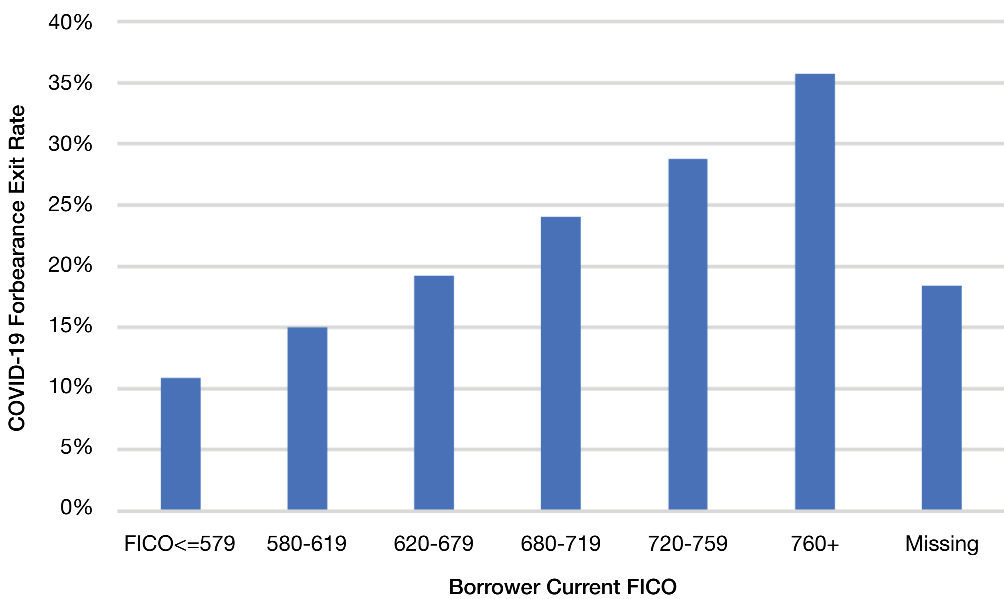
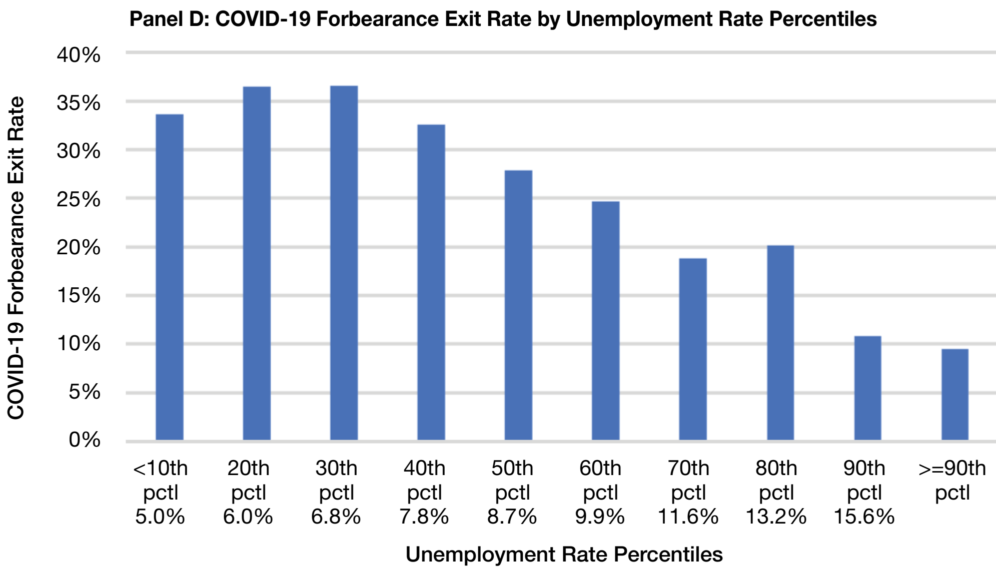


Exhibit 6

Forbearance Exit by Unemployment Rate and Borrower FICO (3 of 3)



EBO = early buyout. FICO = Fair, Isaac and Company credit score. GNMA = Ginnie Mae. GSE =Government sponsored entities. PLS = private-label securitizations.

Notes: EBO are loans bought out of GNMA securities pools. CurrentBeforeExit refers to loans under forbearance that borrowers continued to make payments. ReinstatementAtExit refers to borrowers who did not make all payments but brought the loan to current at exit (called "reinstatement"). CovidDeferral refers to exits where the forborne monthly payments were deferred to loan maturity, refinance, or sale of the property. Modification refers to exits where the borrower exits via a rate or term or a combination modification where monthly payment is reduced after the modification. Other includes less frequent forms including those who exited in delinquent status.

Source: FRB Y-14 data with observation months from Feb. to Dec. 2020, except for February 2020–July 2021 in panel B.

Forms of Forbearance Exits

Borrowers exit forbearance in different forms. First, some forborne borrowers are able to get refinancing (and naturally exit forbearance). Of the 1.0 million borrowers who exited forbearance as of December 2020, 0.11 million, or 11 percent, prepaid at exit.

Exiting for borrowers who have been paying all along under forbearance is straightforward—the principal amortizes as scheduled, and the monthly payment amounts remain intact upon exits. Roughly 0.42 million borrower exits are of this category.

For borrowers who did not make all monthly payments under forbearance, of which there were 0.46 million, they could pay off the accumulated missed monthly payments, bring the loan back to the original amortization schedule in the month of forbearance exits, and resume their regular payment after exits. Approximately 0.15 million borrowers are of this category, also called "reinstatement."

However, such one-time forborne monthly payments at exit are not required for exiting forbearance; a popular form, termed COVID-19 deferral, is to resume prior (to forbearance) monthly payments upon exiting, with the accumulated missed monthly payments due upon maturity, refinance, or property sale.[20] This form does not involve changes in rates or loan terms (and thus monthly payments after forbearance exits remain intact). Approximately 0.23 million borrowers exited in this fashion.

Lastly, a borrower, often unable to exit and resume the original monthly payments, might exit with a modification in terms or rates, or most often in combination, that results in a lower monthly payment. Slightly above 1 percent of all exits were with rate or term modifications from March to December 2020.[21]

Panel B of exhibit 6 plots the number of forbearance exits by exit type using data as of July 2021. Notable is that the exits in earlier months (April–June 2020) were mostly those who were paying under forbearance. In July 2020, exits due to the COVID-19 deferral became the dominant type; within it were mainly GSE loans. Exits via modification appeared late in the sample. The "other" category encompasses exits without these forms of assistance.

Bivariate Analyses

What determines forbearance exits? Bivariate analyses were first conducted and then regression analyses. Panel C of exhibit 6 shows that forbearance exit rates increase with borrower FICO scores; borrowers with FICO scores greater than 760 had exit rates that were close to 3.5 times that of borrowers with FICO scores lower than 580. Shown from a different angle, borrowers who exited earlier had higher FICO scores. For example, the July exits had a median FICO score of 753, and the December exits had a median of 716.

Panel D of exhibit 6 plots the forbearance exit rates by unemployment rate percentile: borrowers in lower unemployment rate counties have higher exit rates. Moving from the 10th to the 90th percentile, borrowers' exit rates decreased by close to two-thirds.

The relationship between the exit rate and borrower credit scores was examined by exit type. The relationship is very close for the exit types of COVID-19 deferral and reinstatement. Prepayment also increased with credit scores, but the relationship was not as strong. Exit by modification does not appear to vary much with credit score. The category Other appears to have a weakly positive relation between exits and credit scores.

In addition, the relationship between the exit rate and unemployment rate was investigated by exit type. Again, the relationship is close for the exit by COVID-19 deferral and reinstatement. Below, in regression analyses, total exits are examined first and individual types of exit are then investigated when applicable.

[20] These deferred payments can be spread across the number of months of missed payments at the end of the original term. For example, suppose the borrower stays in forbearance for 12 months and did not make a single payment. Suppose the monthly pay is $2,000 and the loan is currently year 10 of a 30-year term. The forborne borrower will be expected to pay the $2,000 over the course of 12 months when the term ends. Approximately 20,000 borrowers had explicit extensions of this sort.

[21] Approximately 20,000 borrowers who entered forbearance received modifications as of December 2020; some of these modified loans remained under forbearance.

Regression Analyses of Forbearance Exits

Exhibit 7 shows the regression analyses of forbearance exits. Beyond the explanatory variables used in forbearance entry, an important variable was added: number of months under forbearance. Forbearance termination can be voluntary or caused by expiration of the forbearance plan; including such variables helps capture the impact of forbearance plans.

Exhibit 7

Regressions on Forbearance Exits (1 of 2)

Panel A: Full Sample—All Investors							
Dep. Var.: Forbearance exit by non-prepay		(1)		(2)		(3)	
Variable	Class Value	Estimate	StdErr	Estimate	StdErr	Estimate	StdErr
Intercept		– 1.62	3.24	– 1.89	5.34	– 1.81	5.34
FICO Current (lag)	580–619	– 0.12***	0.01	– 0.13***	0.04	– 0.15***	0.01
(omitted group: <580)	620–679	0.03***	0.01	0.09***	0.03	0.00	0.01
	680–719	0.17***	0.01	0.16***	0.02	0.14***	0.01
	720–759	0.28***	0.01	0.20***	0.02	0.24***	0.01
	760+	0.44***	0.01	0.33***	0.02	0.40***	0.01
	Missing	– 0.49***	0.02	– 0.34***	0.05	– 0.32***	0.02
Unemployment Rate (or UR)		– 0.09***	0.00	– 0.03***	0.00	– 0.04***	0.00
UR*FICO_Curr in	580–619			0.00	0.00		
	620–679			– 0.01***	0.00		
	680–719			0.00	0.00		
	720–759			0.00*	0.00		
	760+			0.01***	0.00		
	Missing			0.00	0.01		
pct_HH_inc>75k						– 0.16**	0.07
UR*pct_HH_inc>75						0.01	0.01
Borrower/loan controls			Yes		Yes		Yes
AUC			0.73		0.76		0.76
Observations				1.53M			

Panel B: Sub-Sample Analyses, by Investors									
Dep. Var.:Exit by non-prepay		GSE		FHA/VA		Portfolio		PLS	
Variable	Class	Estimate	StdErr	Estimate	StdErr	Estimate	StdErr	Estimate	StdErr
Intercept		– 3.38*	1.80	– 4.11	10.70	– 3.34	25.43	– 1.81	1,094.66
FICO_Current (lag)	580–619	– 0.09*	0.06	– 0.27***	0.06	– 0.06	0.10	– 0.26*	0.14
(omitted grp: <580)	620–679	0.00	0.04	0.12**	0.04	0.17**	0.07	0.20*	0.11
	680–719	0.13***	0.03	0.26***	0.05	0.21***	0.07	– 0.02	0.13
	720–759	0.19***	0.03	0.34***	0.05	0.22***	0.07	0.06	0.13
	760+	0.34***	0.03	0.55***	0.04	0.35***	0.05	0.36***	0.12
	Missing	– 0.50***	0.09	– 0.41***	0.08	– 0.55***	0.13	0.15	0.23
Unemployment Rate (UR)		– 0.05***	0.00	– 0.04***	0.00	– 0.04***	0.00	– 0.07***	0.01

Exhibit 7

Regressions on Forbearance Exits (2 of 2)

Panel B: Sub-Sample Analyses, by Investors									
Dep. Var.:Exit by non-prepay		**GSE**		**FHA/VA**		**Portfolio**		**PLS**	
Variable	**Class**	**Estimate**	**StdErr**	**Estimate**	**StdErr**	**Estimate**	**StdErr**	**Estimate**	**StdErr**
UR*FICO_Curr	580–619	0.00	0.01	0.00	0.01	– 0.01	0.01	0.03**	0.01
	620–679	0.00	0.00	– 0.01	0.00	– 0.02**	0.01	– 0.02*	0.01
	680–719	0.00	0.00	0.00	0.01	– 0.02**	0.01	0.01	0.01
	720–759	0.01*	0.00	0.00	0.01	0.00	0.01	0.01	0.01
	760+	0.01***	0.00	0.00	0.00	0.00	0.00	0.00	0.01
Servicer/State fixed effects		Yes		Yes		Yes		Yes	
AUC		0.72		0.77		0.77		0.72	
Observations		508,617		310,516		155,155		62,453	

AUC = Area under the ROC curve. GSE = government sponsored entities. FE = fixed effects. FHA = Federal Housing Administration. VA = Veterans Administration. PLS = private-label securitizations.

Note: Borrower/loan attributes are included.

Source: 10 percent sample of FRBY-14, Feb 2020–Dec 2020

Column 1 of Panel A shows results from a specification where the dependent variable equals 1 if the exit is non-prepay, which comprises reinstatement, deferral, modification, or others. It uses a specification where the lagged payment behavior is fully specified—30+DPD, 60+DPD, etc.[22] Column 2 has the same specification as column 1, except that it includes the interaction between unemployment rate and FICO bins, and column 3 instead includes the interaction with percent of higher income in a ZIP Code. Appendix exhibit A2 presents results using alternative specifications. Specifically, results in appendix exhibit A2 are from a multinomial logit specification where prepayment and non-prepayment exits are treated as competing events.

Shown across columns in Panel A of exhibit 7 (and column 1 in appendix exhibit A2), forbearance exits in the form of non-prepayment increase with borrower credit scores and decrease with past non-payment behavior under forbearance. The exit rate is highest when the borrower has been under forbearance for 6 months, reflecting the CARES Act's mandatory initial forbearance period of 6 months.

The coefficient on unemployment rate in non-prepayment exit is consistently negative at around - 0.03. A 10-percentage point increase in unemployment rate would be associated with a decrease in exit log-odds of 0.3, a magnitude similar to the effect of having a credit score below 580 versus above 760.

Column 2 in Panel A further shows that the response of forbearance exit on unemployment is strongest for borrowers with credit scores of 620–679 and smallest for those with scores above 760. It suggests that borrowers with lower credit scores depend on improvement in the labor market in exiting forbearance more than their higher-score counterparts.[23]

[22] Not all estimated coefficients are shown in the exhibits for brevity reason.

[23] Shown in Column 3, the effect of unemployment on forbearance exit is smaller for borrowers in higher-income ZIP Codes; however, the coefficient is statistically insignificant.

Column 2 in appendix exhibit A2 examines the exit in the form of prepayment (in multinomial logit).[24] The effect of credit scores appears different for prepayment exit versus non-prepayment exit; relative to borrowers with lower credit scores, borrowers with credit scores of 720–759 and 680–719 are relatively more likely to exit via prepayment than they do via non-prepayment exits. Prepayment is examined in more depth later in this report.

Panel B of exhibit 7 presents results from sub-sample analyses of forbearance exits. The reported specification has the interaction between unemployment rates and borrower credit scores. The nonprepayment exits for GSE loans, FHA/VA loans, portfolio loans, and PLS loans were examined, respectively. The four columns show that borrowers with greater credit scores have a higher likelihood of exiting forbearance. Also confirmed is the finding that greater unemployment reduces the exit likelihood across the sub-samples. The smaller impact of the unemployment rate on exit for borrowers with greater credit scores comes from the GSE sub-sample.[25]

The Performance After Forbearance Exits

Summary Statistics

One prominent feature of COVID-19 forbearance is that borrowers who exited can re-enter forbearance. Panel A of exhibit 8 plots the number of borrowers who missed three payments among those who ever entered forbearance. Not surprisingly, the largest chunk of this group were those who were still in forbearance. A small portion of these borrowers were those who re-entered, reflecting that those who found difficulty in paying after exits can request to re-enter.[26] Less than 20,000 forbearance exits and non-re-entrants were in serious delinquency as of December 2020.

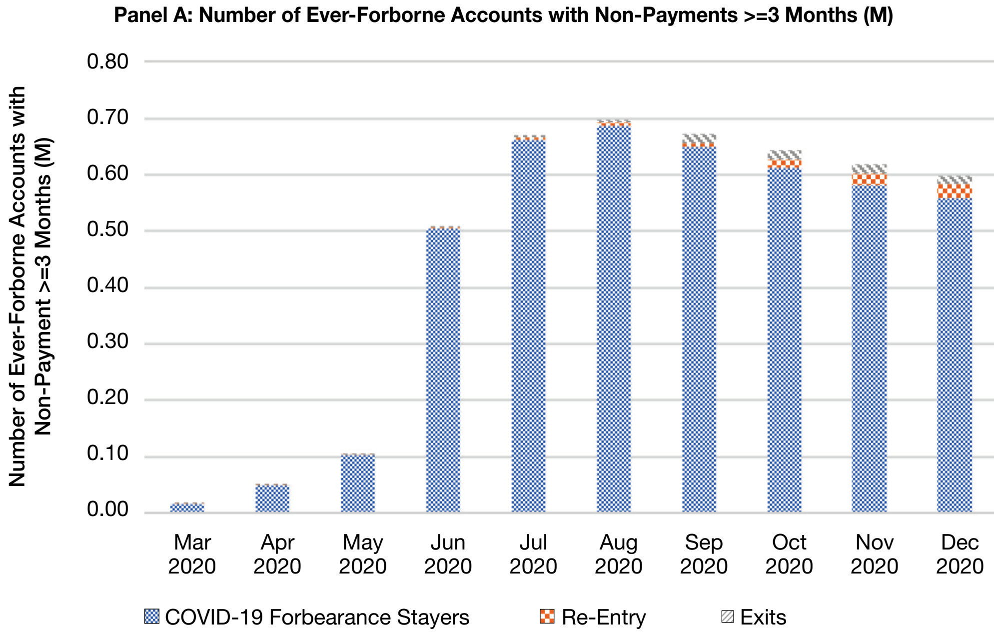
[24] A series of further robustness checks were conducted. First, results are robust to clustering standard errors at the servicer-reporting month level. Second, an alternative way of forming the forbearance exit analysis sample—dropping observations after a loan exits the forbearance—was examined; results are robust to this treatment.

[25] For brevity, servicer fixed effects are not reported. Similar to results for COVID-19 forbearance entry analyses, the servicer fixed effects in COVID-19 forbearance exits are statistically insignificant for GSE and FHA/VA loans but are significant for portfolio loans.

[26] Of the approximately 1 million exits, around 20,000 re-entered.

Exhibit 8

Performance of COVID-19 Forbearance Exits vs Never-forborne Borrowers (1 of 2)



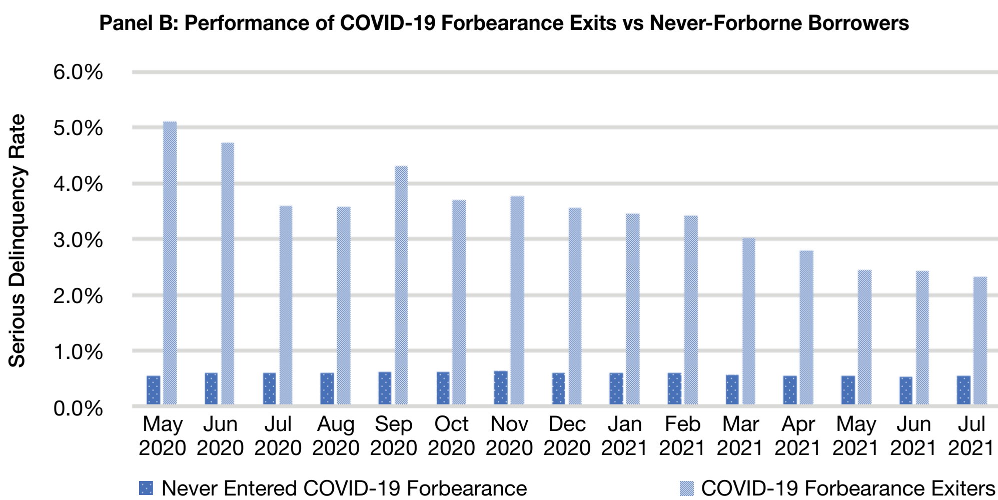
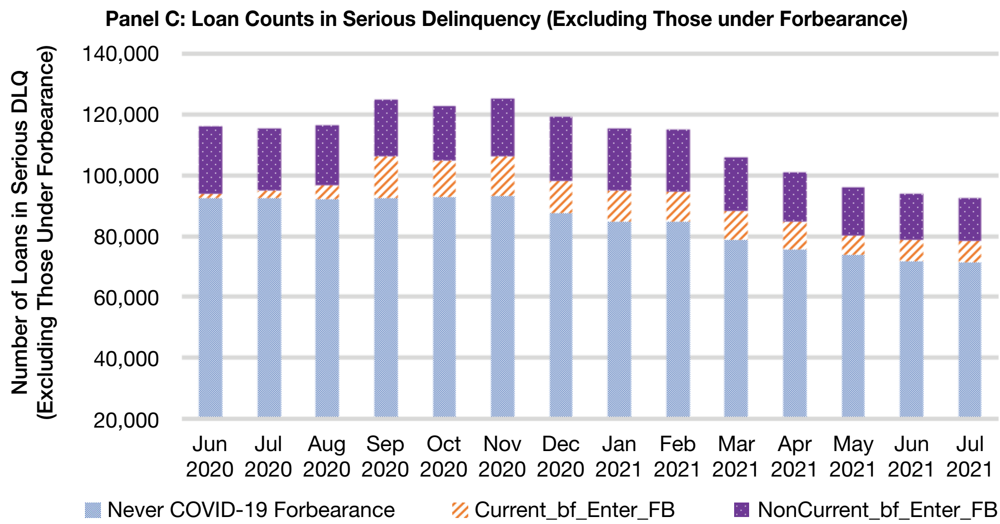


Exhibit 8

Performance of COVID-19 Forbearance Exits vs Never-Forborne Borrowers (2 of 2)



Notes: Re-entry refers to those who have once exited forbearance but re-entered. Serious delinquency is DPD90+ or in foreclosure/REO. NonCurrent_bf_Enter_FB: COVID-19 forbearance exits who were not current before entering forbearance, and so forth.
Source: FRB Y-14 data with observation months from February 2020–July 2021, except for February 2020–December 2020 in Panel A

Regression Analyses

Panel A of exhibit 9 provides results from regression analyses of loan-month observations after a forborne loan exits using performance data as of December 2020. Column 1 shows results where the dependent variable is an indicator variable for re-entry to forbearance, column 2 has an indicator variable for prepayment as the dependent variable, and column 3 has an indicator variable for serious delinquency as the dependent variable. The specification is the same as that in the equation for forbearance entry analyses, except for the dependent variable.

Exhibit 9

Performance Analyses (1 of 2)

Panel A: Loan Performance After COVID-19 Forbearance Exits							
Dep. Var.:		(1) Re-enter Forbearance		(2) PrePay		(3) Serious Delinquency	
Variable	ClassValue	Estimate	StdErr	Estimate	StdErr	Estimate	StdErr
Intercept		– 2.81	6.16	– 15.97	37.40	– 4.88	39.80
FICO_Current (lag)	580–619	0.33***	0.03	– 0.45***	0.12	0.40***	0.03
(omitted grp:<580)	620–679	0.06***	0.02	0.14*	0.08	– 0.15***	0.03
	680–719	– 0.15***	0.02	0.36***	0.07	– 0.50***	0.03
	720–759	– 0.43***	0.02	0.66***	0.07	– 0.80***	0.03
	760+	– 0.67***	0.02	0.51***	0.05	– 1.09***	0.02
	Missing	0.22***	0.05	– 0.42***	0.14	1.03***	0.05

Exhibit 9

Performance Analyses (2 of 2)

Panel A: Loan Performance After COVID-19 Forbearance Exits							
Dep. Var.:		(1) Re-enter Forbearance		(2) PrePay		(3) Serious Delinquency	
Variable	**ClassValue**	**Estimate**	**StdErr**	**Estimate**	**StdErr**	**Estimate**	**StdErr**
Unemployment Rate		0.001	0.003	– 0.003	0.01	– 0.04***	0.00
Servicer & State FE			Yes		Yes		Yes
AUC			0.78		1.00		0.87
Observations				302,255			

Panel B: Performance of Never-Forborne Borrowers vs COVID-19 Forbearance Exits											
Dep. Var: Serious Delinquency	Class Value	All Investors Estimate	StdErr	All Investors Estimate	StdErr	GSE Estimate	StdErr	FHA/VA Estimate	StdErr	Portfolio Estimate	StdErr
Intercept		– 0.46***	0.15	– 1.02***	0.15	– 8.53	28.22	0.18	24.16	– 7.63	10.07
Ever_In_ Forbearance		1.83***	0.01	1.48***	0.02	2.12***	0.03	1.23***	0.02	1.57***	0.04
Dlq_Before_Enter_FB				0.79***	0.02	1.00***	0.03	0.70***	0.03	0.76***	0.05
FICO_ Current (lag)	<=579	1.75***	0.01	1.68***	0.01	1.63***	0.02	1.73***	0.02	1.59***	0.03
Omitted: 720–759	580–619	0.85***	0.01	0.83***	0.01	0.83***	0.03	0.77***	0.02	0.86***	0.04
	620–679	0.03*	0.01	0.05***	0.01	0.00	0.03	– 0.04*	0.02	0.18***	0.03
	680–719	– 0.74***	0.02	– 0.69***	0.02	– 0.68***	0.03	– 0.80***	0.03	– 0.57***	0.04
	760+	– 2.21***	0.02	– 2.20***	0.02	– 2.10***	0.03	– 2.05***	0.04	– 2.08***	0.04
	Missing	1.57***	0.02	1.55***	0.02	1.43***	0.03	1.72***	0.03	1.10***	0.04
Unemployment Rate		0.19***	0.00	0.18***	0.00	0.15***	0.00	0.19***	0.00	0.19***	0.00
AUC		0.92		0.92		0.877		0.93		0.95	
Observations		20.60M		20.60M		13.50M		3.02M		3.26M	

AUC = Area under ROC curve. GSE = government sponsored entities. FE = fixed effects. FHA = Federal Housing Administration. VA = Veterans Administration. PLS = private-label securitizations.

Notes: Re-enter takes the value of 1 if the borrower re-enters COVID-19 forbearance after he/she exits. Serious delinquency is DPD90+ or in foreclosure/REO. Borrower/loan attributes are included.

Source: 10 percent sample of FRB Y-14 data, February 2020–December 2020 for Panel A and February 2020–July 2021 for Panel B

Panel A of exhibit 9 shows that borrowers with higher credit scores are less likely to re-enter forbearance, have a lower serious delinquency rate, and are more likely to prepay. The estimated coefficients indicate that the impact of higher credit scores is larger in reducing serious delinquency rates than in reducing re-entries and that borrowers with credit scores of 720–759 are particularly prone to prepay (more than those with higher than 760).[27]

Shown in Panel A of exhibit 9, the unemployment rate has a statistically insignificant effect on either re-entry or prepay. The coefficient for the unemployment variable in the serious delinquency

[27] The area under ROC (or AUC) for the prepay regression is very high, which arises because the prepayment almost exclusively went to borrowers who had the lowest refreshed loan-to-value ratios (after they exit forbearance).

regression, on the surface, is counter-intuitive, at a negative value. However, this could be caused by borrowers, facing higher unemployment, resorting to forbearance re-entry as a means to manage payments, creating an unusual relationship. The result could also be partially due to the short performance history after borrower exits because the performance data used here are as of December 2020. In next subsection, performance data as of July 2021 were used to further examine performance of borrowers who exited COVID-19 forbearance and compared them with those who never entered.

Comparing Performance of Never Forborne Borrowers versus Forbearance Exits

Loan performance of borrowers who exited forbearance were compared with that of borrowers who never entered forbearance in this subsection.[28] Panel B of exhibit 8 shows that the serious delinquency rate for never-forborne borrowers, in each report month, is at a level lower than 1 percent, whereas the rate for the forbearance exits were around 3 percent (and declining over time). It is worth noting that the number of borrowers who never entered forbearance is the majority.

As a result, excluding those still under forbearance, the number of borrowers in serious delinquency was still mainly from borrowers who had never entered forbearance. In Panel C of exhibit 8, borrower forbearance exits are separated by whether borrowers are delinquent prior to forbearance entrance, and the finding is that those who were already behind in payments prior to forbearance entry persisted in their serious delinquency post-forbearance exits, even as the economy started recovery in 2021.

Panel B of exhibit 9 reports regression results on loan performance using data as of July 2021. The sample of analyses excludes loan-month observations when a borrower is under forbearance; the focus was to compare repayment behavior of those who exited the forbearance with those who never entered. The total number of observation for this analysis is 20.6 million, reflecting the 10 percent random sample of report months from February 2020 to July 2021.

The dependent variable is entering serious delinquency, i.e., it takes the value of 1 when a loan becomes 90 days or more past due or in foreclosure or REO status; the observations after the loan became seriously delinquent were dropped. The explanatory variable of interest is Ever_In_Forbearance, which takes the value of 1 if the loan has ever entered COVID-19 forbearance (and has now exited) and 0 otherwise. The variable Dlq_Before_Enter_FB takes the value of 1 if the borrower is noncurrent prior to entering COVID-19 forbearance and 0 otherwise. A comprehensive list of borrower and loan attributes are included, as in Equation (1); the coefficient on Ever_In_Forbearance thus captures the additional (possibly hard-to-measure) risk factors that are not reflected in the loan and borrower characteristics included in the regressions.

Columns 1 and 2 include all investors, whereas the next three columns focus on GSE loans, FHA/VA loans, and portfolio loans, respectively. Column 1 includes Ever_in_Fobearance alone, and Column 2 includes both variables of interest. The estimated coefficient on Ever_In_Forbearance

[28] Kim et al. (2021) examines the potential information friction in servicers' provision of debt payment reliefs in the COVID-19 pandemic.

was 1.83, at a magnitude very close to that of the borrower having a current FICO score lower than 580 (relative to those with scores ranging from 720 to 759).

In addition, column 2 shows that the coefficient on Ever_In_Forbearance remains positive, and the coefficient on Dlq_Before_Enter_FB is significant positive and with a magnitude of close to that of the borrower having a current FICO score of 580–619 (relative to 720–759). This pattern of findings persists in the sub-sample results by investors. This evidence indicates that borrowers that ever utilized COVID-19 forbearance had higher serious delinquency risk than those who never entered beyond what is captured by typical borrower and loan characteristics.

With the CARES Act provision that credit scores should be not affected by the borrower entering a COVID-19 forbearance program, debates exist on whether credit scores still perform in differentiating borrower default risk as expected. Comparing the results in column (3) of Panel A and results in the first two columns of Panel B indicate that the log-odds of entering serious delinquency by borrowers with current a FICO score (lagged by 1 month) greater than 760 who have exited COVID-19 forbearance are 1.09 lower than those with scores lower than 580, whereas the log-odds of borrowers with current FICO scores greater than 760 in the overall sample were 2.21 lower than those with scores lower than 580, suggesting that current FICO scores have a greater effect on serious delinquency in the general population than in borrowers who experienced and exited COVID-19 forbearance.

The AUC, representing area under the ROC curve, is a measure of the model's discrimination power. It is at 0.87 in column (3) of Panel A, which is lower than that in the first two columns in Panel B, at 0.92. These results hint that while credit score (specifically FICO) is still a strong predictor for loan performance, its ability may have slipped, shown in data from the COVID-19 period. However, drawing a firm conclusion on this trend and assessing the precise magnitude of the drop will require more systematic studies and data with longer performance history, which is outside the scope of this paper.

Unintended Consequence of Forbearance: Reductions in Refinance?

The above analyses highlight the benefits of the forbearance programs: borrowers flocked into the programs in response to a sharp rise in unemployment rate, borrowers with higher credit scores exited it earlier, borrowers in general exited forbearance as the unemployment rate declined, and borrowers who exited the forbearance, despite having serious delinquency rates higher than those who never utilized forbearance, mostly paid (likely with the assistance from deferral programs). In this section, it is examined whether there was a potential unintended consequence of the wide-spread forbearance programs for federally guaranteed or insured mortgages and non-public mortgages as well: by giving a borrower insurance against decline in credit score while not paying under forbearance, as mandated in CARES Act, the program might inadvertently have reduced the borrowers' abilities and opportunities to refinance and thus build greater wealth.[29]

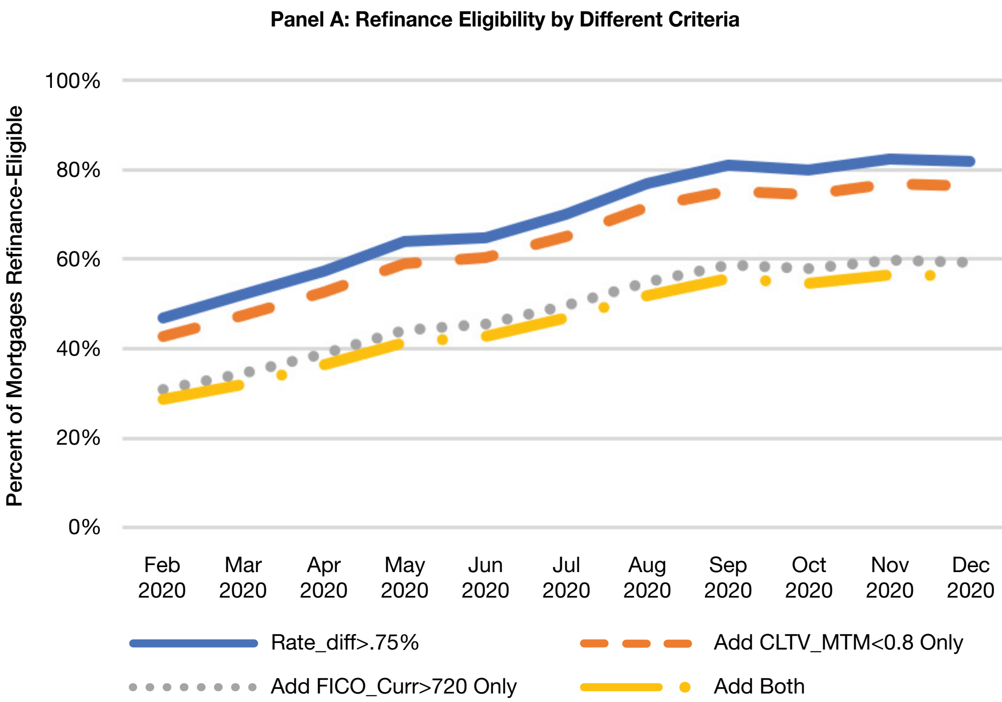
[29] Farrell, Bhagat, Zhao (2019) and Ganong and Noel (2018) examine the role of borrower liquidity and equity in consumer loan defaults.

Summary Statistics

Exhibit 10 examines, whether under COVID-19 forbearance or not, the percent of loans that qualify for a refinance, defined first as the rate difference greater than 75 bps, and then further requiring combined mark-to-market loan-to-value ratio (CLTV_MTM) lower than 0.8 and borrower current FICO scores greater than 720.[30] Panel A shows that FICO, instead of CLTV, restricts the refinance eligibility to a larger degree.

Exhibit 10

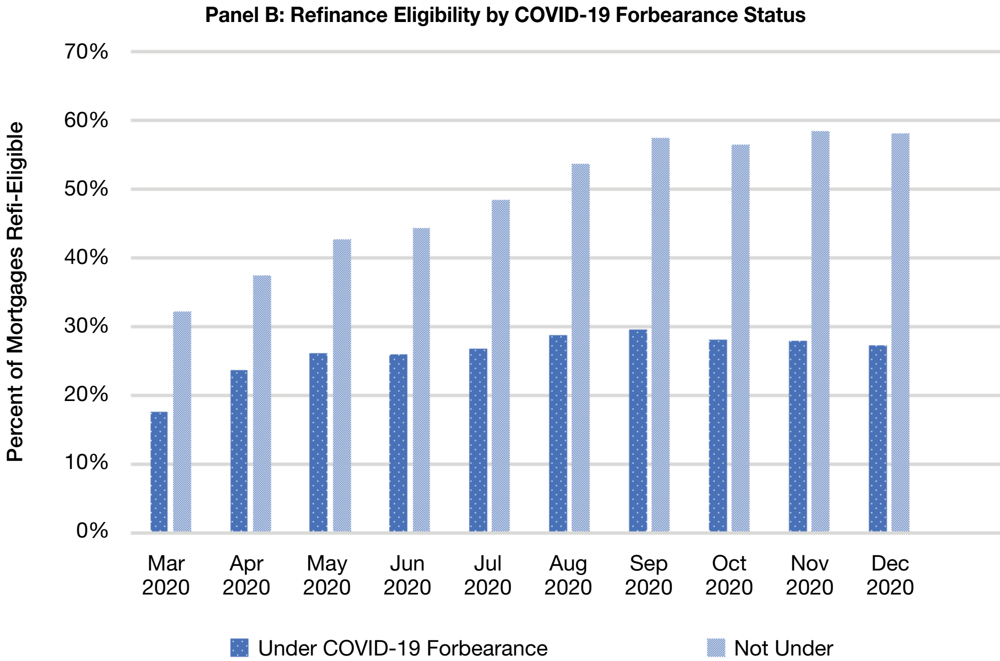
Refinance Eligibility and COVID-19 Forbearance (1 of 2)



[30] The mark-to-market or refreshed property value in Y-14 is the original property value adjusted with the ZIP Code level housing price index changes from the closing month to the reporting month; the HPI was sourced from Loan Processing Services Applied Analytics. The nominator was formed by combining the outstanding principal balance of the first-lien mortgage and the balance of the second-lien mortgage. Lacking details on the amortization of the second lien loan led to the use of the origination amount of the second lien loan; the calculated CLTV is thus an upper bound of the true value.

Exhibit 10

Refinance Eligibility and COVID-19 Forbearance (2 of 2)



Notes: Refinance eligibility is defined first as rate difference greater than 75 bps, and then further requiring loan-to-value ratio lower than 0.8, or borrower FICO scores greater than 720, or both.
Source: FRB Y-14 with observation months from February 2020 to December 2020

Panel B shows that 1) a greater percentage of borrowers not under forbearance were eligible for refinance than those under forbearance, and 2) close to 30 percent of borrowers under forbearance were eligible for refinance, using the most restrictive eligibility definition. However, the lower rate for those under forbearance could be due to lower credit scores. In the regression analyses below, such factors were thus controlled for; how forbearance, especially nonpayment under forbearance, affected refinance likelihood is examined below.

Regression Analyses

Using Forbearance and Payment Status, Lagged by 1 Month

The aim of the examination is whether borrowers' prepayment likelihood varies with the borrower under forbearance and whether he/she pays while under forbearance. The sample for this analysis is thus the full sample. The final number of loan-month observations used in the regression is 16.9 million. The basic econometric specification includes these variables—under forbearance and their payment behavior while under forbearance—besides the basic borrower/loan characteristics variables.

Exhibit 11 shows the regression results; the dependent variable is 1 if the borrower prepays. The first 3 columns used the status of the borrower's forbearance and payment status lagged by 1 month. Column 1 uses all observations, whereas columns 2 and 3 use the sub-sample of federally backed and privately owned mortgages, respectively. The former included those with investors being GSE or GNMA or the loan type being FHA or VA; the latter are the remainder.

Exhibit 11

Impact of Forbearance (and Payment) on Prepay

	(1) Lag 1 month		(2) Lag 1 month		(3) Lag 1 month		(4) Lag 3 months		(5) Lag 3 months	
Dep. Var.: Prepay	All		Federally Backed		Private		Federally Backed		Private	
Intercept	– 4.58***	0.17	– 5.39	4.01	– 4.71***	0.20	– 5.65	5.16	– 4.94***	0.20
FICO Current 580–619	– 0.49***	0.01	– 0.52***	0.02	– 0.41***	0.03	– 0.55***	0.02	– 0.38***	0.03
620–679	– 0.09***	0.01	– 0.09***	0.01	– 0.10***	0.02	– 0.14***	0.01	– 0.13***	0.02
680–719	0.24***	0.01	0.26***	0.01	0.17***	0.02	0.21***	0.01	0.11***	0.02
720–759	0.42***	0.01	0.44***	0.01	0.35***	0.01	0.40***	0.01	0.31***	0.01
760+	0.57***	0.01	0.60***	0.01	0.52***	0.01	0.56***	0.01	0.47***	0.01
Missing	0.05***	0.01	0.03**	0.02	0.10***	0.03	0.20***	0.02	0.18***	0.03
Under_FB (lag)	– 0.85***	0.02	– 0.92***	0.02	– 0.66***	0.04	– 0.25***	0.03	– 0.08	0.05
Current (lag)	– 0.25***	0.02	0.58***	0.03	0.24***	0.05	0.14***	0.03	– 0.19***	0.06
FB (lag)*Current (lag)	0.49***	0.02	– 0.31***	0.02	– 0.11***	0.03	0.30***	0.03	0.41***	0.04
Unemployment rate	– 0.02***	0.00	– 0.02***	0.00	– 0.02***	0.00	– 0.04***	0.00	– 0.03***	0.00
Borrower/Loan controls	Yes		Yes		Yes		Yes		Yes	
State/Svcr fixed effects	Yes		Yes		Yes		Yes		Yes	
AUC	0.65		0.64		0.67		0.65		0.67	
Observations	16.9M		13.6M		3.3M		10.6M		2.6M	

*AUC = Area under the ROC curve. FB = COVID-19 forbearance. FHA = Federal Housing Administration. VA = Veterans Administration. *** = Statistically significant at the 1-percent level.*

Notes: Columns 1–3 use the borrower's COVID-19 forbearance (FB) status and payment status, lagged by 1 month. Columns 4–5 use the borrower's forbearance and payment status, lagged by 3 months.

Source: 10 percent sample of FRB Y-14 data, February–December 2020

Across the columns, borrowers with greater credit scores have a higher likelihood of being prepaid via refinance. On the impact of forbearance status as of last month, it reduces the log-odds of prepayment by 0.85, greater than the impact of the borrower having a credit score of 760+ (relative to those with scores of 579 or less). However, making the payment while under the forbearance greatly alleviated the adverse impact of forbearance on prepay: the log-odds increases by 0.49.

Looking across the private versus the public backed mortgages, such patterns persist with the magnitude smaller for private mortgages.[31]

Possibly anticipating this effect, agencies such as GSEs promulgated policies that greenlighted refinancing for borrowers under forbearance who still pay and borrowers who exit the forbearance and make three consecutive payments (FHFA, 2020). The below analyses use the forbearance and payment status, lagged by 3 months.

Using Forbearance Status, Lagged by 3 Months

Columns 4 and 5 of exhibit 11 show the results, with column 4 examining the federally backed loans and column 5 looking at privately owned loans. Comparing the coefficient on Under_FB (lag) in column 4 with that in column 1 shows that federally backed loans, being in forbearance 3 months prior, have a much weaker negative impact on prepayment likelihood than from being in forbearance 1 month ago. The results for privately owned loans using a 3-month lag in forbearance and payment status are distinct from those using a 1-month lag as well. These results suggest that a distant nonpayment under forbearance has a distinctly less negative impact on refinance probability as an immediate one, particularly for federally backed ones where programs exist to foster refinance accessibility after a borrower's forbearance experience.

Summarizing these results yields the findings that, 1) being in forbearance reduces borrowers' prepayment likelihood, 2) paying under forbearance mitigates the adverse effect of forbearance on borrower prepayment likelihood, and 3) the adverse effect of forbearance on prepayment is diminished when payments are made consecutively, likely reflecting the agency policy that qualifies such a borrower for refinance.

Servicers' Use of Early Buyouts

The majority of this report examines payment relief provided by COVID-19 forbearance to mortgage borrowers. However, servicers are still obligated to remit payments to investors.[32] This section investigates how bank servicers manage the costs associated with servicing borrowers in forbearance. FHA/VA loans have the highest noncurrent rate. For example, across May–September 2020, the noncurrent rate of FHA/VA loans were consistently at 18 percent, and the majority of these nonpaying loans were those under forbearance.

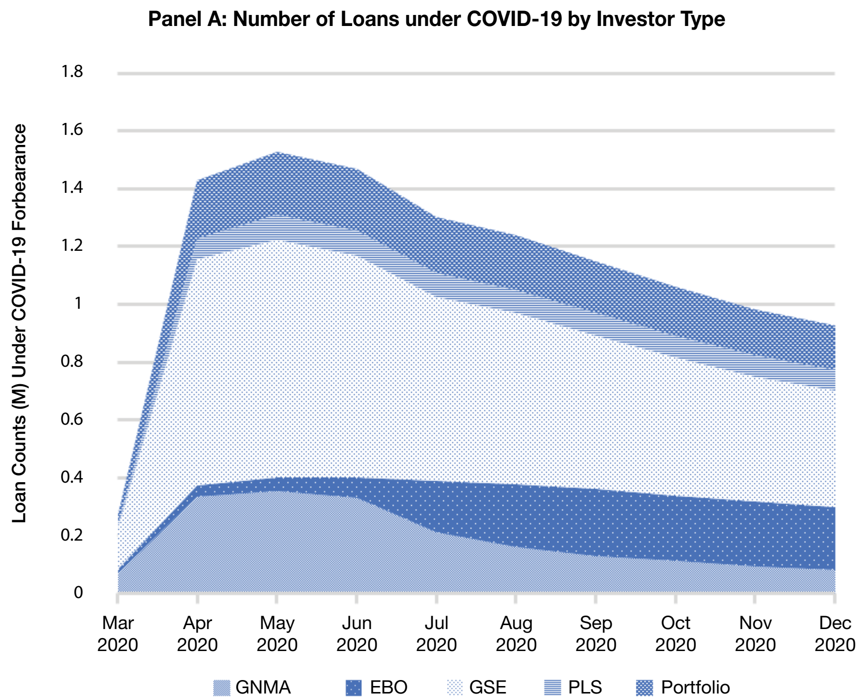
Panel A of exhibit 12 shows that the number of loans in EBO status started to increase in July 2020 and have since stayed elevated; this rise directly coincided with the decline in GNMA loans. Approximately 200,000 borrowers with a combined $40 billion balance are in EBO status as of December 2020.

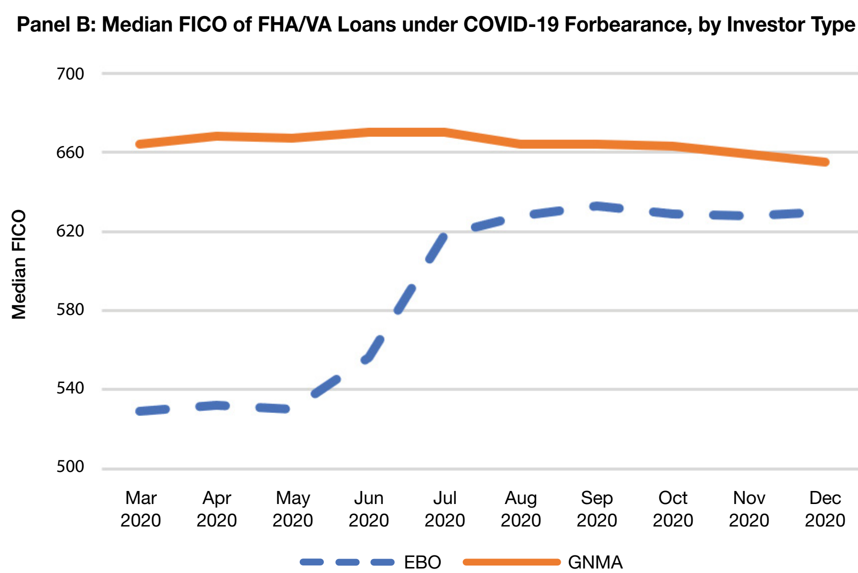
[31] A series of sub-sample analyses were conducted with forbearance and payment status lagged by 1 month; the results suggest that the negative effect of forbearance on prepay and the salvaging effect of payment under forbearance is larger for borrowers with higher credit scores. The negative effect of nonpayment under forbearance is greater for portfolio loans than for FHA loans, but the salvaging effect of payment under forbearance is comparable between portfolio loans and FHA loans.

[32] GSEs and GNMA have policies on the length that servicers face such obligations; programs have also been in place to support servicers.

Exhibit 12

Banks' Use of GNMA Buyouts





EBO = early buyout. GNMA = Ginnie Mae. GSE = government sponsored entities. PLS = private-label securitizations.

Notes: FICO refers to current FICO of borrowers.

Source: FRB Y-14 with observation months from February to December 2020

Panel B of exhibit 12 shows that the median (current) FICO scores of GNMA borrowers under forbearance were at 660 and declined over time, reflecting the exit of borrowers with greater scores. Starting in June 2020 and stabilizing in July 2020, the median borrowers in EBO who were under forbearance sharply increased, from 530 in early 2020 to close to 630 in later 2020, reflecting the fact that FHA/VA borrowers with relatively high credit scores also entered forbearance. Overall, EBO loans have lower FICO scores than GNMA loans, consistent with an interpretation that FHA/VA borrowers with lower credit scores are more adversely affected by the pandemic—utilizing forbearance more and making fewer payments—and thus are disproportionally eligible to be bought out.

Why do servicers engage in buying out loans in GNMA securities and putting them on their own balance sheets? A major factor is the lower funding costs of holding them on balance sheets due to the historically low interest rate during the COVID-19 era. Second, servicers can save the advance expenses that they incur on the nonpaying borrowers, including those under COVID-19 forbearance. Third, servicers can attempt to complete modification/cure and securitize them again, with possible favorable gains upon sale. Further examining of servicers' behavior in the economics of EBO during the COVID-19 era can be a fruitful research area.[33]

Conclusion

This report aims to examine the benefits and the potential costs of the COVID-19 mortgage forbearance programs. Analyzing forbearance entry, exit, and performance after exit using the loan level data serviced by the 18 largest depository servicers yields several findings. First, borrowers with lower credit scores and facing greater unemployment shocks utilized forbearance more; borrowers with greater credit scores exited forbearance faster, and forbearance exits were responsive to an improving labor market; and borrowers' post-forbearance serious delinquency rates were low with the assistance from COVID-19 deferral programs. This evidence suggests that COVID-19 forbearance programs reached those most vulnerable to the economic fallout from the pandemic.

Second, there is heterogeneity in borrowers' entry and exit responses to the unemployment shock; borrowers with the highest credit scores had extra positive entry response to the rise in unemployment rates but were less responsive to improvement in employment in their exits; borrowers with lower credit scores were more responsive to improvement in employment in their exit behavior. These pieces of evidence suggest that although the forbearance programs provided support to borrowers adversely affected by the COVID-19 pandemic, they also allowed some to take precautionary actions or accumulate liquidity; the effect of COVID-19 forbearance programs varies across borrowers.

Third, nonpayment under forbearance had an adverse impact on borrowers' ability to refinance, but this effect was materially alleviated by renewed consecutive payments after exiting forbearance. This evidence highlights the importance of designing policies to provide forborne borrowers opportunities to accumulate wealth while enabling borrowers' payment pauses.

[33] With EBO loans on servicers' balance sheet, whether EBO and GNMA loans perform differently and how loans exit EBO are questions worth examining. These are left for future research when more performance data are available.

There remain many questions unanswered about forbearance: might forbearance generate an unintended consequence of ameliorating borrowers' incentives to look for jobs? Did borrowers utilizing mortgage forbearance to pay down other debts or save them for downpayment for new home purchases and thus contribute to the imbalance in the housing market? These questions are left for future research.

Appendix

Exhibit A1

Estimated Coefficients in COVID-19 Forbearance Entry Baseline Regression (exhibit 4)

Dep. Var.: Forbearance Entry	Class Variable	Estimate	StdErr
Refreshed LTV	Missing	– 0.09**	0.03
(omitted group: <=30)	30–40	– 0.13***	0.01
	40–50	– 0.05***	0.01
	50–60	0.02**	0.01
	60–70	0.09***	0.01
	70–80	0.15***	0.01
	80–90	0.23***	0.01
	90–100	0.35***	0.01
	>100	– 0.24***	0.03
Debt to income	0.15–0.21	– 0.16***	0.01
(omitted group:<0.15)	0.21–0.29	0.00	0.01
	0.29–0.41	0.17***	0.01
	> 0.41	0.32***	0.01
	Missing	– 0.04***	0.01
Loan type (omitted group):	FHA	0.16***	0.01
conventional w/o PMI	VA	– 0.29***	0.01
	Cvtl w PMI	0.06***	0.01
	Other	0.11***	0.01
Status (lag) was Current		– 1.13***	0.01
Loan Purpose	Refi: rate/term	– 0.02	0.02
(omitted group: Purchase)	Refi: cash-out	0.02	0.02
	Refi: home improve	0.02	0.03
	Other	– 0.04*	0.02
Loan Source	Broker	0.27***	0.03
(omitted group: Retail)	Correspondent	0.20***	0.03
	Svcg right purchased	0.12***	0.03
Loan Product	FRM 15 year	– 0.18***	0.01
(omitted group: FRM 30 year)	FRM 40 year	0.17***	0.01
	ARM	– 0.06***	0.01
	Other	0.23***	0.01
Documentation (omitted: full)	Low	0.12***	0.01
	No	0.17***	0.01
	Missing	– 0.66***	0.12
Negative Amortization	Yes	0.20***	0.04
(omitted group: yes)	Missing	– 0.03	0.39
Prepayment Penalty	Yes	– 0.21***	0.02
AUC		0.814	
Observations		17.7M	

*AUC = Area under the ROC curve. FHA = Federal Housing Administration. FRM = fixed rate mortgage. LTV = loan to value ratio. PMI = private mortgage insurance. VA = Veterans Administration. *** = statistically significant at the 1-percent level.*
Source: 10 percent sample of FRBY-14, February 2020–December 2020

Exhibit A2

Robustness Checks on Forbearance Exit Regressions

Dep. Var.:		(1) Forbearance Exit by Non-Prepay		(2) Forbearance Exit by Prepaying	
Variable		**Estimate**	**StdErr**	**Estimate**	**StdErr**
Intercept		– 26.44*	14.96	– 39.29	65.67
FICO Current, lag	580–619	– 0.20***	0.01	– 0.37***	0.06
	620–679	– 0.05***	0.01	– 0.04	0.04
	680–719	0.10***	0.01	0.30***	0.04
	720–759	0.20***	0.01	0.46***	0.04
	760+	0.39***	0.01	0.43***	0.03
	Missing	– 0.07***	0.02	– 0.21***	0.07
Unemployment Rate		-0.06***	0.00	-0.03	0.00
Servicer, State Fixed Effects		Yes		Yes	
Estimation Method		Multinomial Logit		Multinomial Logit	
Observations			1.53 Million		

** = statistically significant at the 10-percent level. *** = statistically significant at the 1-percent level.*
Note: Borrower/loan attributes were included.
Source: 10 percent sample of FRBY-14, February 2020–December 2020.

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Mortgage Appraisal Waivers and Prepayment Speeds

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The analysis and conclusions are those of the authors alone and should not be represented or interpreted as conveying an official position, policy, analysis, opinion, or endorsement of either the Federal Housing Finance Agency or the U.S. government. Any errors or omissions are the sole responsibility of the authors.

Abstract

This report examines factors affecting the use of appraisal waivers for mortgages guaranteed by Fannie Mae and Freddie Mac and the effect of appraisal waivers on prepayment speeds. It shows that the alignment of Freddie Mac's eligibility criteria with those of Fannie Mae around the start of the COVID-19 pandemic was associated with an increase in the use of appraisal waivers. Conditional on satisfying the basic eligibility criteria, appraisal waivers are more common for refinance loans, loans serviced by nonbanks, and less risky borrowers. The report also shows that appraisal waivers were associated with higher conditional prepayment rates during 2020 but to a lesser extent in 2021 as refinancing activity slowed down. Much of this association can be explained by correlations between appraisal waivers and other observable determinants of prepayment speeds.

Introduction

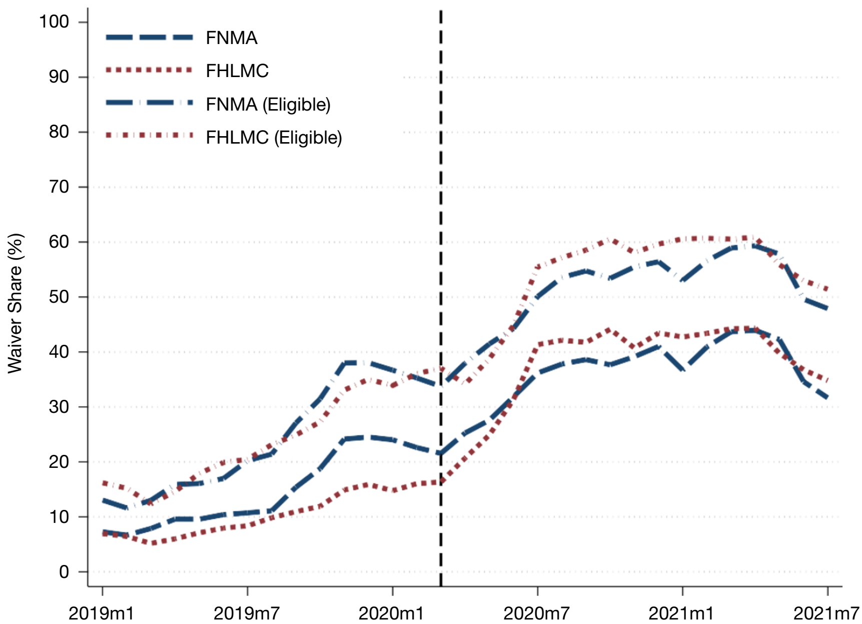
In the context of mortgages, an appraisal waiver is an offer by Fannie Mae or Freddie Mac, which shall be referred to more briefly as "the Enterprises," to a lender and borrower to forgo the requirement of an appraisal, which refers to when the value of the property being purchased using the mortgage is assessed through an inspection.[1] The Enterprise instead assesses the value of the

[1] This report refers to Fannie Mae and Freddie Mac as "the Enterprises" because they are government-sponsored enterprises. The Enterprises guarantee mortgage-backed securities to support the secondary mortgage market. Mortgages must meet certain requirements to be included in a mortgage-backed security guaranteed by the Enterprises. Typically, one such requirement is an appraisal, which is an assessment of the value of the property that serves as collateral for the mortgage.

house using an automated process.[2] Appraisal waivers are becoming more common, and exhibit 1 shows that the share of Enterprise loans underwritten using an appraisal waiver increased from less than 10 percent in early 2019 to more than 30 percent by mid-2021.[3] One factor that may have contributed to the growing use of appraisal waivers in 2020 was the COVID-19 pandemic. For example, to reduce contact between parties in the mortgage transaction process during the early stages of the pandemic, Freddie Mac encouraged the exercise of appraisal waivers for eligible mortgages and expanded its eligibility criteria to more closely align with that of Fannie Mae (Freddie Mac, 2020).

Exhibit 1

Appraisal Waiver Share



FHLMC = Federal Home Loan Mortgage Corporation (Freddie Mac). FNMA = Federal National Mortgage Association (Fannie Mae). m = month. MBS = mortgage-backed securities.

Notes: This exhibit shows the share of appraisal waivers for Fannie Mae and Freddie Mac. It also shows the share for a subsample of loans that were approximately eligible for a waiver. Approximate eligibility is determined by the criteria in exhibit 3 and omitting loans for manufactured housing and co-ops. The dashed line in March 2020 marks the approximate date at which the Enterprises' eligibility criteria were aligned. The date corresponds to the month when a loan's respective MBS pool age is 1 month.

Source: Enterprises' UMBS disclosures accessed via RiskSpan

The increased use of appraisal waivers associated with the pandemic has a number of potential implications for the mortgage market. On the one hand, they could increase the efficiency of

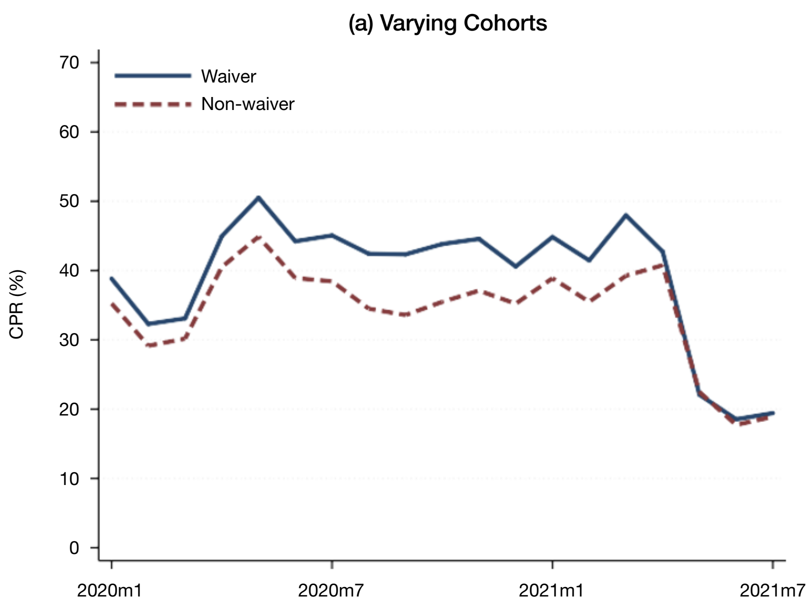
[2] For Fannie Mae, Desktop Underwriter determines appraisal waiver eligibility based in part on an assessment of the quality of prior appraisals recorded in its Collateral Underwriter data (Fannie Mae, 2020). For Freddie Mac, Automated Collateral Valuation determines appraisal waiver eligibility for loans submitted through Loan Product Advisor using historical data, public records, and models (Freddie Mac, n.d.).

[3] Fannie Mae introduced its current appraisal waiver program in December 2016 (Fannie Mae, 2016), and Freddie Mac followed in 2017 (Freddie Mac, 2017b).

mortgage transactions by reducing the time and costs associated with the appraisal process.[4] On the other hand, these efficiency gains could also be associated with higher prepayment speeds, as exhibit 2 shows that loans that originated with an appraisal waiver exhibited a higher conditional prepayment rate (CPR) throughout 2020.[5] Prepayment speeds are important for several reasons. First, they affect the value of mortgage-backed securities (MBS). Second, market participants have indicated that the alignment of prepayment speeds across cohorts of the Enterprises' uniform MBS (UMBS) is crucial to maintaining their fungibility in the to-be-announced (TBA) market, which is a key goal of the UMBS Rule (Federal Housing Finance Agency, 2019).[6,7] Third, if the relationship between prepayments and appraisal waivers is persistent and causal, then failing to price the use of an appraisal waiver creates a cross-subsidy in favor of borrowers who use an appraisal waiver.[8]

Exhibit 2

Prepayment Speeds by the Use of Appraisal Waivers (1 of 2)



[4] Appraisal waivers are estimated to reduce loan closing times by about 7 to 10 days and appraisal costs by $300 to $700 (FHFA OIG, 2018). Lenders also enjoy relief from representations and warranties on the value, condition, and marketability of the property (Fannie Mae, 2022; Freddie Mac, n.d.), which reduces the risk of being required by the guaranteeing Enterprise to repurchase the loan.

[5] The conditional prepayment rate is the percentage of a loan's principal that is estimated to be prepaid, or paid before the loan is due.

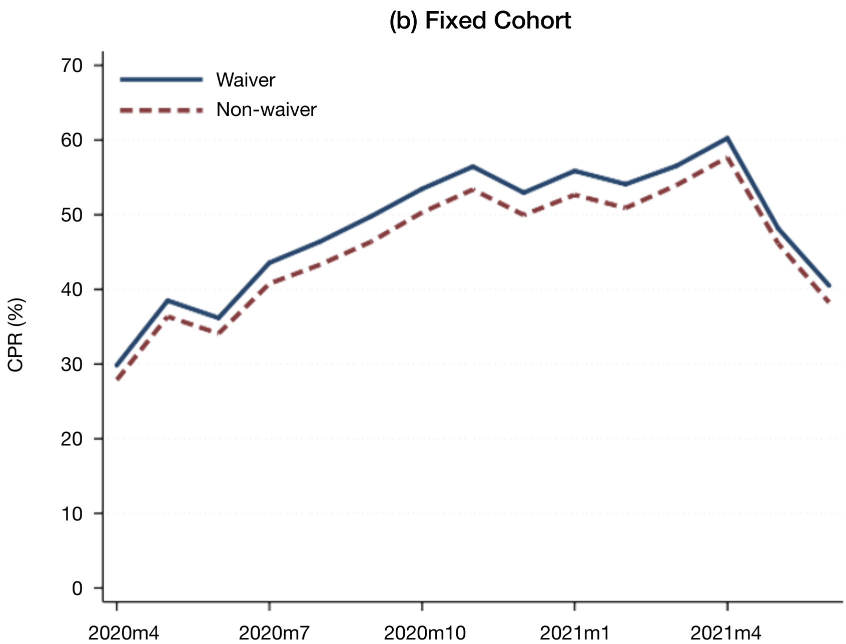
[6] A uniform MBS is an MBS with the same structure regardless of which Enterprise issues it. The TBA market is a forward market for mortgage-backed securities guaranteed by the Enterprises, in which details about the security—including the issuing Enterprise in the case of UMBS—is revealed only shortly before delivery.

[7] The incidence of appraisal waivers at the two Enterprises generally became more similar after the alignment of the eligibility criteria, which does not indicate any adverse effects for UMBS.

[8] Borrowers who use an appraisal waiver are arguably better off because they can satisfy the eligibility criteria (exhibit 3). In addition, section 2 shows that appraisal waivers are more common for borrowers with high credit scores and low debt-to-income ratios.

Exhibit 2

Prepayment Speeds by the Use of Appraisal Waivers (2 of 2)



CPR = conditional prepayment rate. LTV = loan-to-value. m = month.

Notes: Exhibit 2a shows the average CPR for loans with and without an appraisal waiver. The date corresponds to the month when a loan's respective MBS pool age is 12 months. Exhibit 2b shows the average CPR for loans with and without an appraisal waiver within the set of purchase mortgages in the Freddie Mac 2019 3.0 coupon cohort, with a loan size between $200,000 and $400,000, FICO score greater than 720, and LTV less than 80.

Source: Enterprises' UMBS disclosures accessed via RiskSpan

This report first examines several factors that have affected the use of appraisal waivers. For a loan to be underwritten with an appraisal waiver, it first must meet the eligibility criteria of the guaranteeing Enterprise, which is typically given by an upper limit of the loan-to-value (LTV) ratio depending on the loan purpose and occupancy type (see exhibit 3).[9] The Enterprise must then determine whether to offer a waiver. Finally, the waiver must be accepted by both the borrower and the lender. Before 2020, Freddie Mac's appraisal waiver eligibility criteria were stricter than Fannie Mae's. On March 29, 2020, Freddie Mac expanded its eligibility criteria for cash-out refinances and rate-term (or "no cash-out") refinances to match the criteria of Fannie Mae more closely.[10] The expansion of Freddie Mac's eligibility criteria seems to have been associated with an increase in appraisal waivers. However, many loans that meet the LTV limits still do not use an appraisal waiver. Among loans satisfying the limits, appraisal waivers are more common for refinance loans, nonbank servicers, and high credit score borrowers.[11]

[9] Various additional factors can affect eligibility. See Fannie Mae (2022) and Freddie Mac (2022) for further details.

[10] It specifically extended eligibility to cash-out refinance loans with an LTV up to 70 percent for primary residences or 60 percent for secondary residences, and it raised the LTV limit for rate-term refinance loans from 80 percent to 90 percent for both primary and secondary residences. See Freddie Mac (2020). Note that Freddie Mac's eligibility criteria were not exactly aligned with Fannie Mae's, as they remained stricter for investment properties.

[11] The term *nonbanks* refers to financial institutions that do not have deposits.

Exhibit 3

Appraisal Waiver Eligibility Criteria

	Fannie Mae	Freddie Mac before March 29, 2020	Freddie Mac after March 29, 2020
Purchase			
Primary residence	80%	80%	80%
Second Home	80%	80%	80%
Investment Property	Ineligible	Ineligible	Ineligible
No cash-out refinance			
Primary residence	90%	80%	90%
Second Home	90%	80%	90%
Investment Property	75%	Ineligible	Ineligible
Cash-out refinance			
Primary residence	70%	Ineligible	70%
Second Home	60%	Ineligible	60%
Investment Property	60%	Ineligible	Ineligible

Notes: This exhibit presents the loan-to-value limits across loan purpose and occupancy types to qualify for an appraisal waiver. See Fannie Mae (2022) and Freddie Mac (2022) for details on other factors affecting eligibility. For announcements regarding updates to Fannie Mae's eligibility criteria, see Fannie Mae (2020) and, particularly, Fannie Mae (2016) for the introduction of appraisal waivers for refinances; and Fannie Mae (2017) for the expansion of appraisal waivers to purchase loans. Fannie Mae (2018) also provides a summary of the eligibility criteria for Fannie Mae. For announcements regarding updates to Freddie Mac's eligibility criteria, see Freddie Mac (2017b) for the introduction of appraisal waivers for rate-term refinances, Freddie Mac (2017a) for the expansion of appraisal waivers to purchase loans, and Freddie Mac (2020) for the expansion of the eligibility criteria for appraisal waivers in March 2020.

Sources: Fannie Mae and Freddie Mac

This report then examines explanations of the association between appraisal waivers and prepayment speeds. During 2020, appraisal waivers were associated with a 6.7-percentage-point increase in CPRs by the time a loan's respective pool is 12 months old. However, about 78 percent of this association can be explained by correlations between appraisal waivers and other observable determinants of prepayment speed. For example, borrowers with higher credit scores or previous refinancing experience are less likely to wait too long to refinance when interest rates are low (Agarwal, Rosen, and Yao, 2015), and loans originated by nonbanks are generally associated with faster prepayments (Buchak et al., 2018; Fuster et al., 2019). After controlling for observable loan, borrower, and servicer characteristics, appraisal waivers were associated with a 1.5-percentage-point increase in CPRs. The residual association is stronger for purchase loans than refinance loans, consistent with appraisal waivers mitigating inconveniences involved in refinancing. In particular, refinances are more likely to be associated with borrowers who already have a low barrier to refinance and thus less to gain from the efficiency benefits of an appraisal waiver. Finally, the association between appraisal waivers and prepayment speeds diminished around April 2021, simultaneously with a general decrease in refinancing incentives. The observation that appraisal waivers are more strongly associated with prepayment speeds when refinancing incentives are high is consistent with lenders prioritizing loans that are more likely to use an appraisal waiver when faced with capacity constraints.

Prior Research

This report is related to recent research papers on the prevalence and implications of appraisal waivers. For example, Karamon and McManus (2022) find that appraisal waivers are associated with lower default risk among Freddie Mac loans. This report also contributes to a literature on the determinants of mortgage prepayment speeds. Buchak et al. (2018) find that nonbanks are generally associated with faster prepayments. Fuster et al. (2019) additionally show that the subset of nonbank lenders with a fully online application process, also known as fintechs, are associated with higher market-wide local refinancing propensities, possibly due to improving the efficiency of the mortgage transaction process. Agarwal, Rosen, and Yao (2015) find that borrowers who have refinanced before make smaller refinancing errors.

For more general background on research on appraisal waivers, as early as 2018, industry analysts expressed concern about the effects of appraisal waivers on prepayment speeds, speculating that technological changes at the Enterprises focused on streamlining the origination process, including appraisal waivers and digital verification of assets, income, and employment, could increase prepayment speeds much like streamlined refinance options had increased prepayment speeds for Federal Housing Administration (FHA), Veteran's Administration (VA), Rural Housing Service (RHS), and Public and Indian Housing (PIH) loans.

Industry analysts initially used loan-level disclosures associated with the Enterprises' credit risk transfer securities, particularly Fannie Mae's Connecticut Avenue Securities (CAS) and Freddie Mac's Structured Agency Credit Risk (STACR) securities, to draw preliminary conclusions about the prevalence of appraisal waiver loans by acquiring Enterprise, loan purpose, originator type, loan or borrower characteristics, and geography. Questions raised in analysts' research reports and complaints of inadequate disclosures spurred the Enterprises under FHFA coordination to release loan-level data on appraisal waivers in their monthly MBS disclosures in March 2020, with retrospective data going back to January 2017 for Fannie Mae and to June 2017 for Freddie Mac. The data release enabled further analysis to understand the implications of appraisal waivers for prepayment risk and the value of credit risk transfer (CRT) issuances and UMBS.

Appraisal Waiver Prevalence

This section shows that the expansion of Freddie Mac's appraisal waiver eligibility criteria to align with those of Fannie Mae was associated with an increase in the use of appraisal waivers. It also shows that, controlling for eligibility, appraisal waivers are more common for refinances, nonbank servicers, and high credit score borrowers.

Data

This analysis uses the Enterprises' UMBS monthly public disclosures provided by RiskSpan.[12] It focuses on new MBS issuances from January 2019 to July 2021. In particular, each observation corresponds to a loan when its respective MBS pool age is 1 month. This analysis omits Fannie Mae refinance loans before July 2019, as the data do not distinguish between cash-out and rate-term

[12] The data are provided by RiskSpan with the Enterprises' loan-level public disclosure as the original source.

refinances. It uses a 10-percent random sample from the resulting set of loans. Exhibit 4 presents summary statistics for servicer, loan, borrower, and timing characteristics. About 31 percent of loans in the sample used an appraisal waiver.

Graphical Analysis of Appraisal Waiver Prevalence

This section documents several facts about how the use of appraisal waivers has varied over time based on various loan, servicer, and borrower characteristics.

Exhibit 4

Summary Statistics for Appraisal Waiver Prevalence Analysis

	N	Mean	SD	P25	P75
Waiver	1,461,155	0.312	0.463	0.000	1.000
FHLMC	1,461,155	0.448	0.497	0.000	1.000
Purchase	1,461,155	0.389	0.487	0.000	1.000
Rate-term	1,461,155	0.406	0.491	0.000	1.000
Cash-out	1,461,155	0.205	0.404	0.000	0.000
Nonbank	1,461,155	0.599	0.490	0.000	1.000
FICO	1,461,155	754.587	43.180	725.000	790.000
DTI (%)	1,461,155	34.011	9.743	27.000	42.000
LTV (%)	1,461,155	72.396	17.381	61.000	84.000
Amount ($1,000s)	1,461,155	272.069	132.091	171.000	353.000
Post	1,461,155	0.711	0.453	0.000	1.000

Notes: Waiver *indicates whether a loan used an appraisal waiver.* FHLMC *indicates whether the loan was acquired by Freddie Mac.* Purchase *indicates whether the loan was a purchase loan.* Rate-term *indicates whether the loan was a rate-term refinance.* Cash-out *indicates whether the loan was a cash-out refinance.* FICO *is the FICO credit score.* DTI *is the debt-to-income ratio.* LTV *is the loan-to-value ratio on origination.* Amount *is the loan amount in thousands of dollars.* Post *indicates months after March 2020 when there was an alignment of appraisal waiver eligibility criteria between Freddie Mac and Fannie Mae.*

Source: Enterprises' UMBS disclosures accessed via RiskSpan

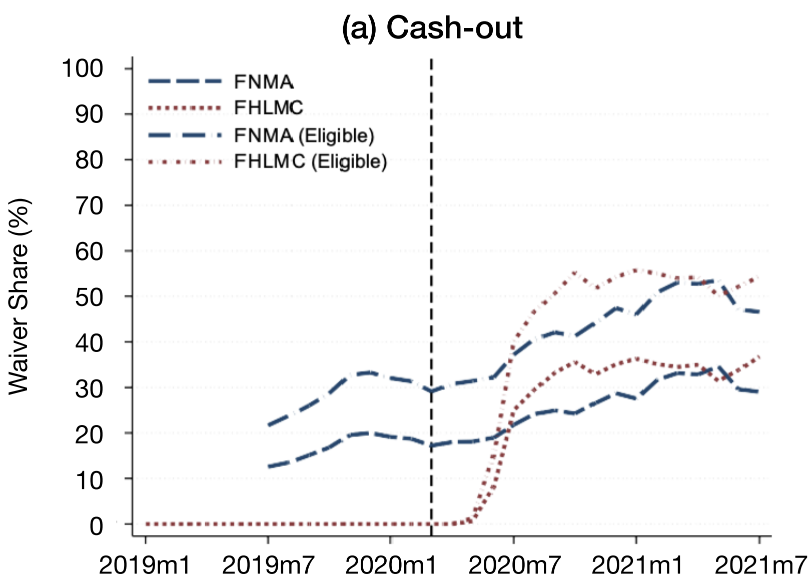
As noted earlier, exhibit 1 shows that the use of appraisal waivers for both Enterprises increases dramatically from 2019 to 2020. Consistent with the alignment of the Enterprises' eligibility criteria in March 2020, Freddie Mac had a lower rate before the update but then caught up with Fannie Mae afterward.

To further distinguish the role of the Enterprises' eligibility criteria compared with other factors, this analysis restricts to an approximate set of loans satisfying the eligibility criteria. In particular, this sample consists of loans satisfying the LTV limits to be eligible for an appraisal waiver, as described in exhibit 3, and omits loans for manufactured housing and co-ops, which are ineligible based on the additional criteria mentioned in Fannie Mae (2022) and Freddie Mac (2022). This sample may include some ineligible loans because some potential determinants of eligibility are unobserved. Restricting to the set of eligible loans yields additional insights. First, the fact that the gap in appraisal waiver shares between the Enterprises in 2019 largely closed for the set of eligible loans provides additional evidence that Freddie Mac exhibited a lower appraisal waiver share during this time primarily because of its more restrictive eligibility requirements. Second, the waiver share generally remained below 60 percent, which suggests that factors other than eligibility had a substantial effect on the use of appraisal waivers.[13]

Exhibit 5 compares the prevalence of appraisal waivers for different loan purpose categories. Exhibit 5a indicates that the appraisal waiver share for Freddie Mac loans increased especially dramatically for cash-out refinance loans shortly after Freddie Mac expanded its eligibility criteria, increasing from virtually zero in March 2020 to around 35 percent in November. Exhibit 5b shows that the alignment of the Enterprises' eligibility criteria was also associated with an acceleration in the use of appraisal waivers for rate-term refinance loans, as reflected in the convergence between the appraisal waiver shares for the full sample and the subsample of eligible loans. By contrast, the appraisal waiver share for purchase loans, which are not affected by the alignment of the eligibility criteria, increased more modestly. By mid-2021, the appraisal waiver share was only around 10 percent for purchase loans compared with around 60 percent for rate-term refinance loans. Differences in the strictness of eligibility within loan purpose groups can explain some differences. In particular, after the alignment of the Enterprises' eligibility criteria, both Enterprises required only a 10-percent down payment for a refinance loan but required a 20-percent down payment for a purchase loan. However, sizable differences remain even when restricting to the set of eligible loans.

Exhibit 5

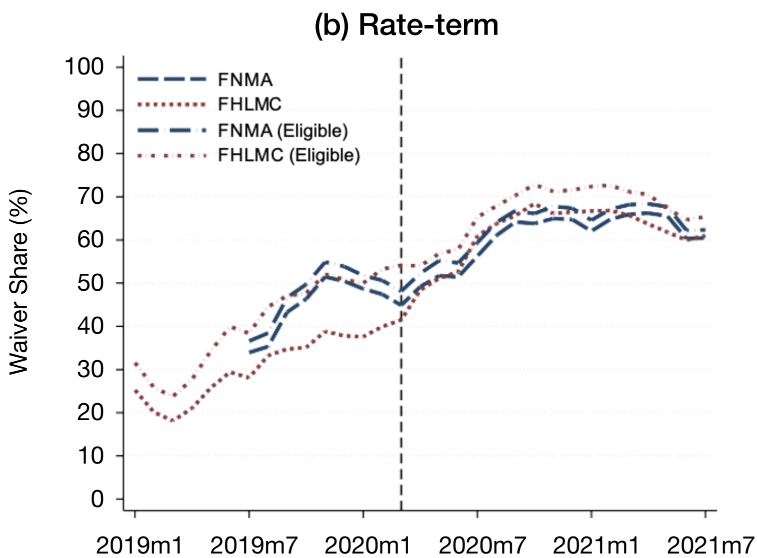
Appraisal Waiver Share by Loan Purpose (1 of 2)

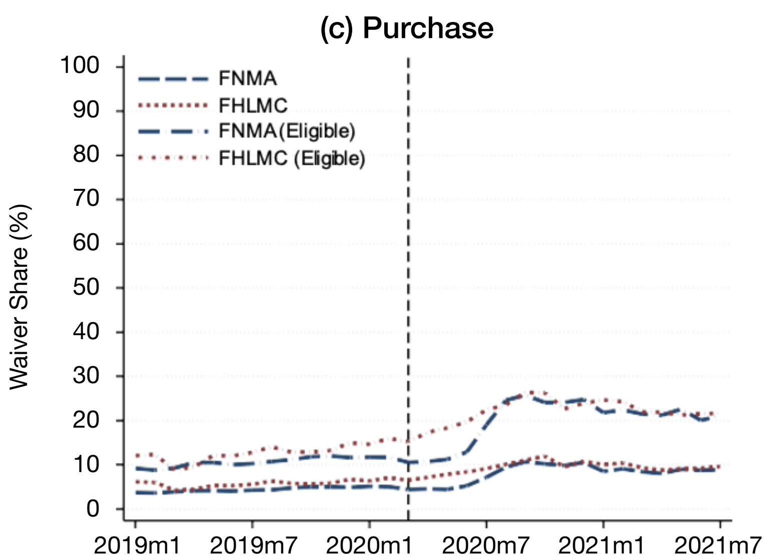


[13] Reasons for ineligibility that are not observed may have also limited waiver share.

Exhibit 5

Appraisal Waiver Share by Loan Purpose (2 of 2)





FHLMC = Federal Home Loan Mortgage Corporation (Freddie Mac). FNMA = Federal National Mortgage Association (Fannie Mae). m = month.

Notes: This exhibit shows the share of appraisal waivers for Fannie Mae and Freddie Mac for purchase loans, share-term refinances, and cash-out refinances and for a subsample of loans that were approximately eligible for a waiver within each of these groups. Approximate eligibility is determined by the loan-to-value limits in exhibit 3 and omitting loans for manufactured housing and co-ops. The dashed line in March 2020 marks the approximate date at which the Enterprises' eligibility criteria were aligned. Note that some series are curtailed because the data for Fannie Mae do not distinguish between cash-out and rate-term refinances before July 2019. The date corresponds to the month when a loan's respective MBS pool age is 1 month.

Source: Enterprises' UMBS disclosures accessed via RiskSpan

Exhibit 6 compares the prevalence of appraisal waivers based on whether the servicer is a bank or a nonbank. For both Enterprises, nonbanks generally exhibited higher rates of appraisal waivers.

Nonbank servicers of Freddie Mac loans increased the share of appraisals particularly dramatically after the alignment of the Enterprises' eligibility criteria, although the difference between bank and nonbank servicers diminished starting in late 2020. When restricting to the set of eligible loans, the difference between banks and nonbanks widens, particularly for Freddie Mac.

The larger gap for the set of eligible loans suggests that nonbanks tend to more often underwrite loans that are ineligible, even though they are also more likely to use an appraisal waiver for eligible loans. Consistent with these aggregate results, exhibit 7 shows that the appraisal waiver shares of loans acquired by Freddie Mac for United Wholesale Mortgage and Quicken Loans, the two largest nonbank servicers in the sample, increased abruptly in 2020 and peaked at around 90 percent and 70 percent, respectively. The appraisal waiver share at Wells Fargo, the largest bank servicer, generally increased more gradually and evenly between the two Enterprises.

Exhibit 6

Appraisal Waiver Share by Servicer Type: Bank vs. Nonbank (1 of 2)

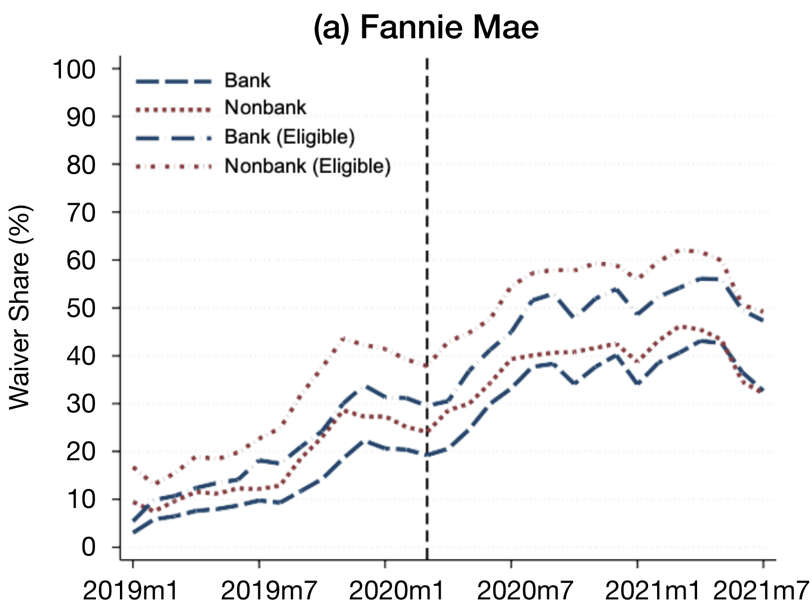
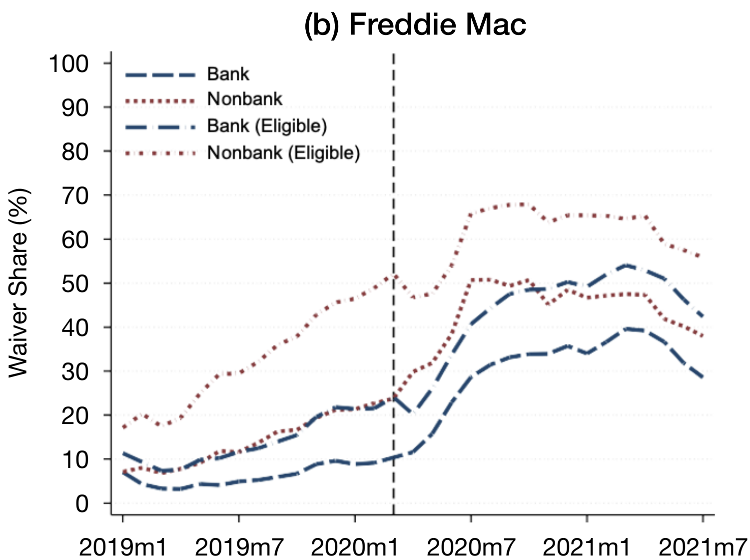


Exhibit 6

Appraisal Waiver Share by Servicer Type: Bank vs. Nonbank (2 of 2)



FHLMC = Federal Home Loan Mortgage Corporation (Freddie Mac). FNMA = Federal National Mortgage Association (Fannie Mae). m = month.

Notes: This figure shows the share of appraisal waivers for Fannie Mae and Freddie Mac for loans serviced by banks and nonbanks and for a subsample of loans that were approximately eligible for a waiver within each of these groups. Approximate eligibility is determined by the loan-to-value limits in exhibit 3 and omitting loans for manufactured housing and co-ops. The dashed line in March 2020 marks the approximate date at which the Enterprises' eligibility criteria were aligned. The date corresponds to the month when a loan's respective MBS pool age is 1 month.

Source: Enterprises' UMBS disclosures accessed via RiskSpan

Exhibit 7

Appraisal Waiver Share for United Wholesale Mortgage, Quicken, and Wells Fargo (1 of 2)

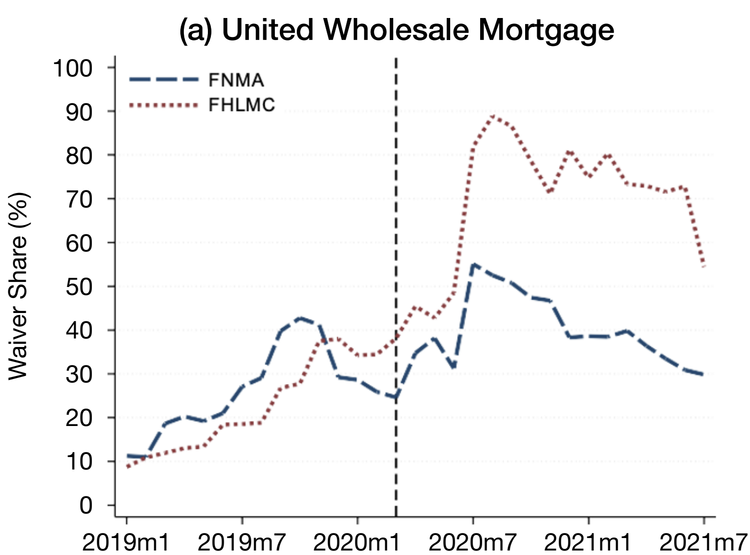
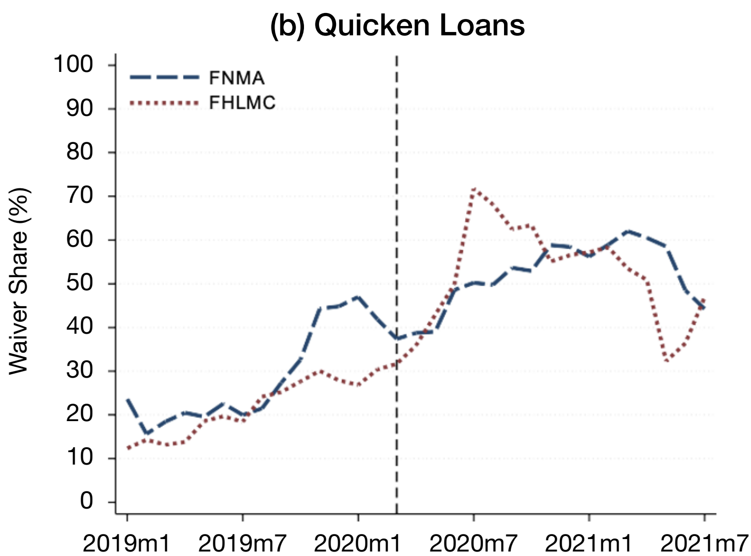
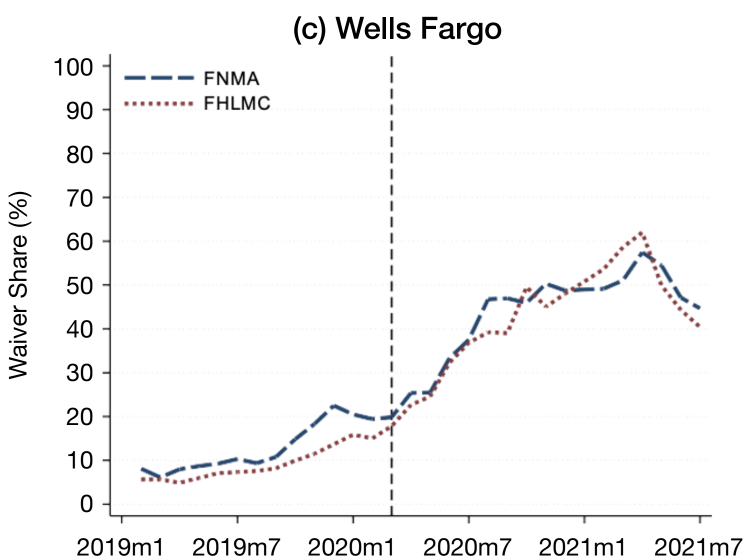


Exhibit 7

Appraisal Waiver Share for United Wholesale Mortgage, Quicken, and Wells Fargo (2 of 2)





FHLMC = Federal Home Loan Mortgage Corporation (Freddie Mac). FNMA = Federal National Mortgage Association (Fannie Mae). m = month.

Notes: This exhibit shows the share of appraisal waivers for Fannie Mae and Freddie Mac for United Wholesale Mortgage, Quicken Loans, and Wells Fargo. The dashed line in March 2020 marks the approximate date at which the Enterprises' eligibility criteria were aligned. The date corresponds to the month when a loan's respective MBS pool age is 1 month.

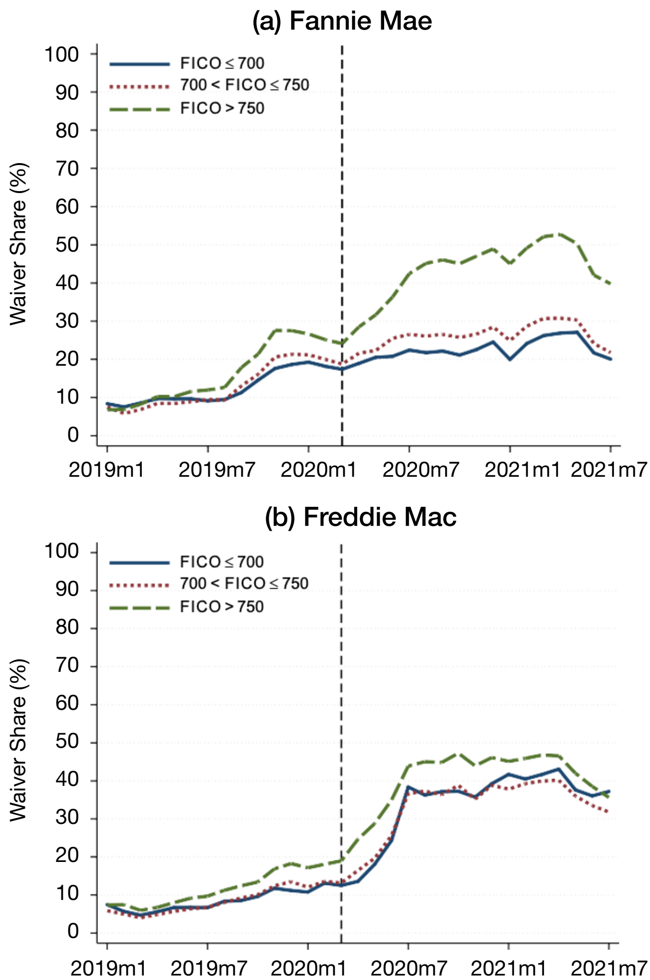
Data source: Enterprises' UMBS disclosures accessed via RiskSpan

Exhibit 8 compares the prevalence of appraisal waivers based on the borrower's credit score. Credit score does not determine eligibility for an appraisal waiver, but it could be correlated with factors that do affect eligibility, such as the LTV ratio, or it could affect the willingness of an Enterprise, borrower, or lender to all agree to an appraisal waiver conditional on the loan satisfying the eligibility criteria. Whereas both Enterprises have higher appraisal waiver shares for loans with FICO scores above 750, Freddie Mac has a notably higher share for loans with FICO scores below 750. In addition, both Enterprises exhibit little differentiation in appraisal waiver shares between loans with FICO scores below 700 and loans with FICO scores between 700 and 750.

The Appraisal Waiver Prevalence: Additional Results section in the appendix shows the association between appraisal waivers and various additional attributes.

Exhibit 8

Appraisal Waiver Share by FICO



FICO = Fair Isaac Corporation. m = month. MBS = mortgage-backed securities.

Notes: This exhibit shows the share of appraisal waivers for Fannie Mae and Freddie Mac for loans with FICO scores of 700 and lower, 701 through 750, and greater than 750. The dashed line in March 2020 marks the approximate date at which the Enterprises' eligibility criteria were aligned. The date corresponds to the month when a loan's respective MBS pool age is 1 month.

Source: Enterprises' UMBS disclosures accessed via RiskSpan

Regression Analysis

This section implements a regression analysis to assess the joint association between appraisal waivers and many of the characteristics considered in the Graphical Analysis of Appraisal Waiver Prevalence section. For example, that section shows that appraisal waivers are more common for refinance loans and loans serviced by nonbanks, but this association could be driven by correlations with other characteristics that are also associated with the use of appraisal waivers, such as risk, loan amount, or location.

This analysis estimates variations of the following specification:

$$100 * waiver_{it} = \beta_1 FHLMC_{it} + \beta_2 rateterm_{it} + \beta_3 cashout_{it} + \beta_4 nonbank_{it} + \gamma \boldsymbol{X}_{it} + \psi_t + \epsilon_{it} \tag{1}$$

where $waiver_{it}$ indicates whether an appraisal waiver was used for loan i, whose respective pool has an age of 1 month at month t; $FHLMC_{it}$ indicates whether the loan was acquired by Freddie Mac; $rateterm_{it}$ indicates whether the loan is a rate-term refinance; $cashout_{it}$ indicates whether the loan is a cash-out refinance; $nonbank_{it}$ indicates whether the servicer is a nonbank; $\boldsymbol{X}_{it}$ is a set of controls that includes FICO score, debt-to-income ratio, loan-to-value ratio, the logarithm of the loan amount, and indicators for occupancy type and state; ψ_t indicates month fixed effects; and ϵ_{it} is the error term.

Column 1 of exhibit 9 shows the results from estimating a baseline version of equation (1) during the period before the alignment of the Enterprises' eligibility criteria, which corresponds to January 2019 to March 2020. Consistent with the figures in the Graphical Analysis of Appraisal Waiver Prevalence section, refinance loans and loans serviced by nonbanks exhibit a higher appraisal waiver share, whereas loans acquired by Freddie Mac exhibit a lower appraisal waiver share. Column 2 restricts to the set of loans satisfying the basic eligibility criteria, in which case there is a notably stronger association between appraisal waivers and nonbanks. In addition, the association between appraisal waivers and Freddie Mac becomes slightly positive. Column 3 adds the control variables. Appraisal waivers are more likely to be used for loans that appear to be safer in some respects, such as having a higher credit score or lower debt-to-income ratio, although they are also more likely to be used for loans with higher LTV ratios conditional on satisfying the eligibility limits.

They are also associated with higher loan amounts. In terms of magnitudes, appraisal waivers are 30 percent more common for rate-term refinance loans compared with purchase loans, 12 percent more common for cash-out refinance loans compared with purchase loans, 10 percent more common for loans serviced by a nonbank compared with loans that are not, and 3 percent more common for Freddie Mac loans.

Exhibit 9

Determinants of Appraisal Waiver Prevalence

	1 Pre	2 Pre	3 Pre	4 Post	5 Post	6 Post
FHLMC	-4.541***	0.814***	0.317*	1.505***	3.020***	2.371***
	(-46.09)	(4.25)	(1.68)	(17.97)	(27.76)	(22.08)
Rate-term	33.666***	32.657***	31.010***	52.380***	42.921***	40.763***
	(207.90)	(156.92)	(143.83)	(608.46)	(322.26)	(290.81)
Cash-out	2.060***	13.796***	13.731***	18.244***	22.389***	20.929***
	(19.37)	(41.29)	(38.87)	(170.34)	(128.52)	(111.86)
Nonbank	5.472***	11.315***	9.467***	6.658***	10.077***	9.435***
	(57.47)	(63.11)	(52.20)	(78.19)	(89.43)	(83.21)
FICO			0.052***			0.133***
			(26.04)			(104.99)
DTI			-0.076***			-0.128***
			(-8.52)			(-23.52)
LTV			0.054***			0.006
			(7.85)			(1.45)
Log (amount)			3.076***			-0.338***
			(16.81)			(-2.73)
Observations	422,545	212,025	212,025	1,038,610	736,082	736,082
R^2	0.196	0.165	0.198	0.248	0.139	0.185
Eligible sample	No	Yes	Yes	No	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	No	Yes	No	No	Yes
Occupancy FE	No	No	Yes	No	No	Yes

DTI = debt-to-income. FE = fixed effects.

Notes: This exhibit presents results from estimating variations of the regression equation $100 * waiver_{it} = \beta_1 FHLMC_{it} + \beta_2 rateterm_{it} + \beta_3 cashout_{it} + \beta_4 nonbank_{it} + \gamma X_{it} + \psi_t + \epsilon_{it}$, *where* $waiver_{it}$ *indicates whether an appraisal waiver was used for loan* i, *whose respective pool has an age of 1 month at month t;* $FHLMC_{it}$ *indicates whether the loan was acquired by Freddie Mac;* $rateterm_{it}$ *indicates whether the loan is a rate-term refinance;* $cashout_{it}$ *indicates whether the loan is a cash-out refinance;* $nonbank_{it}$ *indicates whether the servicer is a nonbank;* X_{it} *is a set of controls that includes FICO score, debt-to-income ratio, loan-to-value ratio, the logarithm of the loan amount, and indicators for occupancy type and state;* ψ_t *indicates month fixed effects; and* ϵ_{it} *is the error term. Column (1) estimates a baseline specification for all loans in the period before the Enterprises' eligibility criteria were aligned (January 2019 to March 2020). Column (2) restricts to the subsample of loans that were approximately eligible for an appraisal waiver. Approximate eligibility is determined by the loan-to-value limits in exhibit 3 and omitting loans for manufactured housing and co-ops. Column (3) adds controls. Columns (4)–(6) are analogous for the period from April 2020 to July 2021. T-statistics computed using heteroskedasticity-consistent standard errors are reported in parentheses. *indicates statistical significance at the 10-percent level, **indicates significance at the 5-percent level, and ***indicates significance at the 1-percent level.*

Source: Enterprises' UMBS disclosures accessed via RiskSpan

Columns 4–6 estimate an analogous series of regressions except for the period after the alignment of the Enterprises' eligibility criteria, which corresponds to April 2020 to July 2021. The association between appraisal waivers and nonbanks or Freddie Mac is similar compared with the earlier period, and both types of refinance loans become even more strongly associated with appraisal waivers compared with purchase loans. In particular, appraisal waivers became 41 percent more common for rate-term refinance loans than purchase loans and 21 percent more common for cash-out refinance loans. Appraisal waivers also appear to be more strongly associated with safer loans, as the positive correlation with credit score and the negative correlation with the debt-to-income ratio both increased in magnitude and the positive correlation with the LTV ratio diminished. However, the association between appraisal waivers and loan size diminished.[14]

[14] Additional unreported results show that larger servicers are positively associated with the use of appraisal waivers both before and after the change of the eligibility criteria.

Appraisal Waivers and Prepayment Speeds

This section first outlines hypotheses for how appraisal waivers could be associated with faster prepayment speeds. It then shows that other determinants of prepayment speeds can explain much but not all of the positive association between appraisal waivers and faster prepayment speeds. Finally, it presents evidence consistent with the efficiency gains of appraisal waivers leading to faster prepayment speeds by showing that the association is stronger for purchase loans and during periods when refinancing activity is high.

Hypotheses

Appraisal waivers could be associated with faster prepayments due to a joint correlation with observables, a joint correlation with unobservables, or a direct causal relationship. Identifying the source of the association is important for public and business policy purposes. In the first case, directly controlling for the appraisal waiver share at each Enterprise is not likely to be important to ensure prepayment alignment, as UMBS investors and the Enterprises can instead assess prepayment risk based on the underlying causes. One argument that appraisal waivers are correlated with, but do not cause, increased prepayment speeds is based on the observation that loans that are eligible for an appraisal waiver are generally less risky, as they must satisfy limits on the LTV ratio that are particularly strict for cash-out refinances, secondary homes, and investment properties. In particular, loans with low LTVs and collateralized by primary residences may be likely to prepay faster because they are subject to less stringent underwriting standards and are more likely to be offered attractive interest rates.[15]

If, however, the relationship between appraisal waivers and prepayment speeds cannot be explained by observable characteristics, then a key question is how the use of an appraisal waiver in a previous refinancing could be independently predictive of a loan's prepayment speed. On the one hand, appraisal waivers could be associated with faster prepayment speeds due to a joint correlation with unobservables. For example, a borrower who accepts an appraisal waiver offer may generally be more proactive about financial opportunities. On the other hand, appraisal waivers could directly cause faster prepayment speeds.[16] For example, a borrower who uses an appraisal waiver for the first time may come to believe that it reduces the hassle of the mortgage transaction process, which could reduce the anticipated inconvenience of future refinances. In addition, servicers may solicit refinances more aggressively to borrowers who used an appraisal waiver on their existing loan, as they might expect such borrowers to be more likely to accept an appraisal waiver in future transactions and therefore yield the associated efficiency benefits.[17]

Data

As in the Appraisal Waiver Prevalence section, this analysis uses RiskSpan data for loans included in MBS that were issued from January 2019 to July 2021. It measures prepayment speeds using the

[15] Gerardi, Willen, and Zhang (2020) find that the LTV ratio is negatively associated with prepayment due to refinancing.

[16] The relevance of identifying a direct causal effect may depend on the application. For MBS pricing, the implications are similar as long as appraisal waivers predict repayment speeds independently of observable characteristics.

[17] Aside from efficiency, lenders also benefit from relief from representations and warranties on the value, condition, and marketability of the property.

conditional prepayment rate (CPR), which is an estimate of the portion of a loan's principal that is likely to be repaid early. Because the CPR for newly issued loans shows relatively little variation, the main sample instead focuses on loans in MBS pools with an age of 12 months. This analysis uses a 10-percent random sample from this set of loans. Exhibit 10 presents summary statistics for all these characteristics in the sample used for this analysis.[18] The average CPR at 12 months is about 33 percent.

Exhibit 10

Summary Statistics for Prepayment Speed Analysis

	N	Mean	SD	P25	P75
CPR (%)	600,424	32.851	19.086	17.384	50.054
Waiver	600,424	0.208	0.406	0.000	0.000
FHLMC	600,424	0.435	0.496	0.000	1.000
Purchase	600,424	0.467	0.499	0.000	1.000
Rate-term	600,424	0.334	0.472	0.000	1.000
Cash-out	600,424	0.199	0.399	0.000	0.000
Nonbank	600,424	0.551	0.497	0.000	1.000
FICO	600,424	751.518	43.469	722.000	787.000
DTI (%)	600,424	34.645	9.654	28.000	43.000
LTV (%)	600,424	74.630	17.144	65.000	89.000
Amount ($1,000s)	600,424	257.216	123.149	164.000	333.000
Coupon (%)	600,424	3.024	0.645	2.500	3.500
Post	600,424	0.363	0.481	0.000	1.000

Notes: CPR *is the conditional prepayment rate.* Waiver *indicates whether a loan uses an appraisal waiver (property inspection waiver).* FHLMC *indicates whether the loan is acquired by Freddie Mac.* Purchase *indicates whether the loan is a purchase loan.* Rate-term *indicates whether the loan is a rate-term refinance.* Cash-out *indicates whether the loan is a cash-out refinance.* FICO *is the FICO credit score.* DTI *is the debt-to-income ratio.* LTV *is the loan-to-value ratio on origination.* Amount *is the loan amount in thousands of dollars.* Coupon *is the coupon.* Post *indicates months starting in April 2021.*

Source: Enterprises' UMBS disclosures accessed via RiskSpan

Graphical Analysis of Prepayment Speeds

Exhibit 2a shows the average CPR for pools with an age of 12 months for loans with or without an appraisal waiver. In 2020, which corresponds to loans issued in 2019, the loans with an appraisal waiver exhibited a CPR of about 3 to 9 percentage points higher. To graphically assess whether using an appraisal waiver causes a loan to prepay faster than other loans with similar credit and borrower characteristics, exhibit 2b shows the prepayment speeds for purchase mortgages included in the Freddie Mac 2019 3.0 coupon cohort with a FICO score greater than 720, LTV less than or equal to 80 percent, and loan size between $200,000 and $400,000. Consistent with exhibit 2a, loans with a prior appraisal waiver exhibited a higher CPR throughout 2020, although the difference in 2b is smaller than the one in 2a.[19]

[18] Restricting to older loans reduces the sample size compared to that of the Appraisal Waiver Prevalence section.

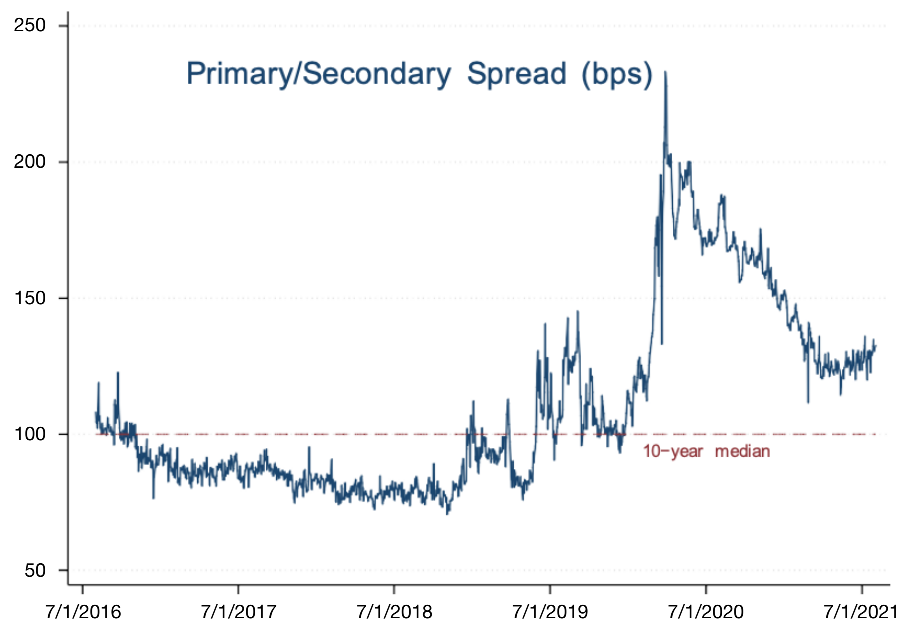
[19] There is also some variation among servicers. For example, additional unreported results show that appraisal waivers are associated with faster prepayment speeds for United Wholesale Mortgage and Wells Fargo for at least part of the sample period but not as much for Quicken Loans.

The exhibits also show that the average CPR and the increase in CPRs associated with appraisal waivers simultaneously diminished starting around April 2021. One potential explanation is that, during 2020, historically low mortgage interest rates brought about an environment in which lenders and appraisers became so capacity-constrained that loans with appraisal waivers may have been prioritized due to their shorter processing time. In particular, lenders may have anticipated that borrowers who used an appraisal waiver on their existing loan would be more likely to accept an appraisal waiver in future transactions. Beginning in the second quarter of 2021, as refinance applications started to decline, lenders and appraisers became less capacity-constrained, and the efficiency advantages of an appraisal waiver became less urgent.

For additional evidence on the role of capacity constraints, a typical benchmark is the primary/secondary (P/S) spread, as shown in exhibit 11.[20] The long-term historical P/S spread is around 100 basis points (bps). Beginning in the second half of 2019, as mortgage rates started to decline, the P/S spread jumped from 80 bps to as high as 140 bps. Since then, the P/S spread continued moving up and reached a historic high of over 200 bps before settling around 130 bps during the first half of 2021, indicating a relaxation of capacity constraints. This relaxation of capacity constraints is simultaneous with the diminishing association between appraisal waivers and prepayment speeds, which is consistent with the explanation that appraisal waivers have a larger effect on prepayment speeds when lenders face capacity constraints.

Exhibit 11

Mortgage Primary/Secondary Spread



bps = basis points.
Source: Bloomberg

[20] Fuster, Lo, and Willen (2017) show that the price of intermediation is positively associated with application volume, consistent with capacity constraints.

Regression Analysis

This section generalizes the approach in exhibit 2b by estimating a regression to assess how appraisal waivers affect prepayment speeds while controlling for a variety of servicer, borrower, and loan characteristics.

This analysis estimates variations of the following specification:

$$CPR_{it} = \beta_1 waiver_{it} + \beta_2 FHLMC_{it} + \beta_3 rateterm_{it} + \beta_4 cashout_{it} + \beta_5 nonbank_{it} + \gamma \boldsymbol{X}_{it} + \psi_t + \epsilon_{it} \quad (2)$$

Where CPR_{it} indicates the CPR for a loan i, whose MBS pool age is 12 months in month t; $waiver_{it}$ indicates whether the loan used an appraisal waiver; $FHLMC_{it}$ indicates whether the loan was acquired by Freddie Mac; $rateterm_{it}$ indicates whether the loan is a rate-term refinance; $cashout_{it}$ indicates whether the loan is a cash-out refinance; $nonbank_{it}$ indicates whether the servicer is a nonbank; $\boldsymbol{X}_{it}$ is a set of controls that includes FICO score, debt-to-income ratio, loan-to-value ratio, the logarithm of the loan amount, the coupon, and indicators for occupancy type and state; and ψ_t indicates issue month fixed effects.[21, 22]

Column 1 of exhibit 12 shows the results from estimating a baseline version of equation (2) from January 2020 to March 2021—up to the shift in April 2021. Consistent with exhibit 2a, appraisal waivers were associated with faster prepayment speeds by a margin of about 6.7 percent. When controls are added in Column 2, the association becomes weaker but remains positive and significant, with an appraisal waiver being associated with a 1.5-percent-higher CPR. Column 2 also shows that prepayment speed is positively associated with both types of refinances, nonbanks, and Freddie Mac.[23]

Column 3 shows that appraisal waivers have a relatively weaker effect on prepayment speeds for refinances and Freddie Mac loans.

The stronger effect of appraisal waivers on prepayment speeds for purchase loans is consistent with the hypothesis that appraisal waivers mitigate barriers to refinance. In particular, existing refinance loans may tend to prepay faster when interest rates are low because the borrowers already have a relatively low barrier to refinance. An appraisal waiver has relatively little effect on these borrowers because they are more likely to refinance when it is profitable. By contrast, a borrower of a purchase mortgage may be more likely to perceive more hassle associated with applying for refinancing, even if it is profitable. A borrower who uses an appraisal waiver may come to view the

[21] This analysis focuses on the CPR when the MBS pool age is 12 months because CPRs at shorter durations exhibit less variation and are more concentrated near zero. Additional unreported results show qualitatively similar, albeit somewhat smaller, results when estimating a specification with observations for each loan and month while also including issue month x CPR month fixed effects.

[22] Additional unreported results show qualitatively similar, albeit somewhat smaller, results when including servicer fixed effects instead of an indicator for nonbanks.

[23] The positive association between refinance loans and prepayments during a low-interest-rate environment is consistent with Agarwal, Rosen, and Yao (2015), who find that borrowers with previous refinancing experience are less likely to wait too long to refinance. The positive association between nonbanks and refinance loans is similar to the findings in Buchak et al. (2018), who use the Fannie Mae and Freddie Mac Single Family Loan Performance Data, and Fuster et al. (2019), who use Equifax's Credit Risk Insight Servicing McDash data.

mortgage transaction process as less of a hassle, which could increase the propensity to refinance when it is profitable.

Columns 4 to 6 estimate an analogous series of regressions except for the period from April 2021 to July 2021. The association between appraisal waivers and prepayment is much weaker, although it is still positive and statistically significant. The effect of appraisal waivers on prepayment speeds continues to be strongest for purchase loans.

Exhibit 12

Determinants of Prepayment Speed

	1 Pre	2 Pre	3 Pre	4 Post	5 Post	6 Post
Waiver	6.708*** (79.55)	1.501*** (20.90)	2.259*** (12.79)	0.864*** (15.88)	0.544*** (9.61)	1.365*** (8.00)
FHLMC		1.048*** (22.14)	1.166*** (22.73)		0.542*** (10.75)	0.511*** (7.73)
Rate-term		1.522*** (23.85)	1.730*** (24.56)		1.499*** (22.55)	1.631*** (22.03)
Cash-out		1.943*** (27.69)	1.962*** (27.02)		2.314*** (26.96)	2.311*** (24.68)
Nonbank		5.253*** (105.77)	5.157*** (96.98)		3.768*** (69.95)	3.951*** (58.61)
Waiver × HLMC			-1.114*** (-8.30)			0.143 (1.46)
Waiver × Rate-term			-1.347*** (-8.19)			-0.668*** (-4.03)
Waiver × Cash-out			-0.955*** (-3.95)			-0.228 (-1.10)
Waiver × Nonbank			0.922*** (6.64)			-0.591*** (-5.80)
Observations	382,195	382,195	382,195	218,228	218,228	218,228
R^2	0.037	0.452	0.453	0.258	0.429	0.429
Issue Month FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	Yes	No	Yes	Yes
Occupancy FE	No	Yes	Yes	No	Yes	Yes
Controls	No	Yes	Yes	No	Yes	Yes

Notes: This exhibit presents results from estimating variations of the regression equation $CPR_{it} = \beta_1 waiver_{it} + \beta_2 FHLMC_{it} + \beta_3 rateterm_{it} + \beta_4 cashout_{it} + \beta_5 nonbank_{it} + \gamma X_{it} + \psi_t + \epsilon_{it}$, *where* CPR_{it} *indicates the CPR at an* MBS *pool age of 12 months for a loan* i *at month* t*;* $waiver_{it}$ *indicates whether the loan used an appraisal waiver;* $FHLMC_{it}$ *indicates whether the loan was acquired by Freddie Mac;* $rateterm_{it}$ *indicates whether the loan is a rate-term refinance;* $cashout_{it}$ *indicates whether the loan is a cash-out refinance;* $nonbank_{it}$ *indicates whether the servicer is a nonbank;* X_{it} *is a set of controls that includes FICO score, debt-to-income ratio, loan-to-value ratio, the logarithm of the loan amount, the coupon, and indicators for occupancy type and state;* ψ_t *indicates issue month fixed effects; and* ϵ_{it} *is the error term. Column 1 estimates the baseline correlation between CPR and the use of appraisal waivers with only issue month fixed effects during the period from January 2020 to March 2021, column 2 adds controls, and column 3 adds interactions of* $waiver_{it}$*. Columns 4–6 are analogous for the period from April 2021 to July 2021. T-statistics computed using heteroskedasticity-consistent standard errors are reported in parentheses. *indicates statistical significance at the 10-percent level. **indicates significance at the 5-percent level. ***indicates significance at the 1-percent level.*

Source: Enterprises' UMBS disclosures accessed via RiskSpan

Conclusion

This report shows that the use of appraisal waivers is affected by not only the Enterprises' eligibility criteria but also various loan, servicer, and borrower characteristics, such as loan purpose, nonbank status, and credit score. These characteristics can explain much but not all of the association between appraisal waivers and prepayment speeds. This analysis also presents evidence that the efficiency advantages of appraisal waivers could also contribute to prepayment speeds, as the association with prepayment speeds is weaker for refinancing loans, which are more likely to be made by borrowers who already have low barriers to refinance, and stronger when refinancing incentives are high, in which case lenders are more likely to face capacity constraints. These hypotheses regarding the effect of appraisal waivers on prepayment speeds could be further tested using more detailed data distinguishing the decisions of borrowers and lenders to accept or reject an appraisal waiver offer, which is left for future research. Another consideration for future research is to further examine the relative speeds at which different lenders adapted to the change in the appraisal waiver eligibility conditions, perhaps with a specific focus on the agility of fintechs or the needs of lenders specializing in rural housing.

Appendix

Appraisal Waiver Prevalence: Additional Results

This section extends the graphical analysis of appraisal waiver prevalence from the Graphical Analysis of Appraisal Waiver Prevalence section to an additional set of attributes.

Exhibit A-1 shows that appraisal waivers are more common for borrowers with lower debt-to-income (DTI) ratios, particularly less than 35 percent, even though DTI does not directly affect appraisal waiver eligibility.

Exhibit A-1

Appraisal Waiver Share by Debt-to-Income Ratio (1 of 2)

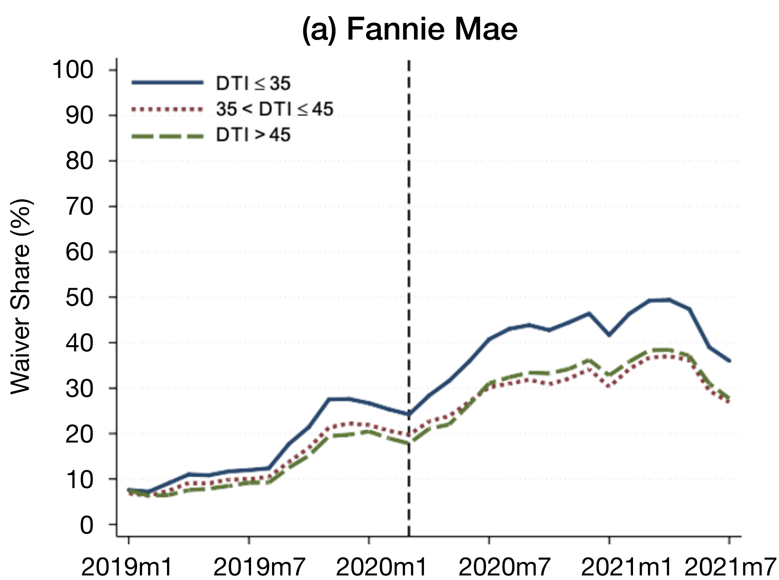
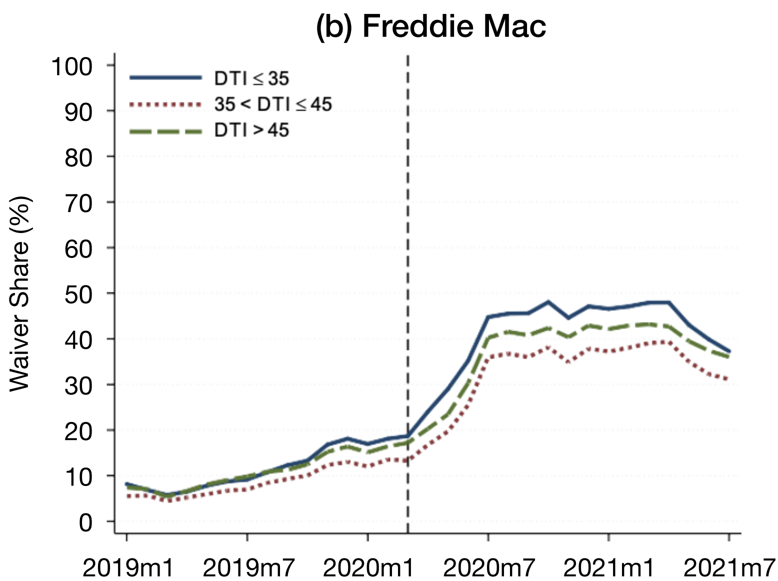


Exhibit A-1

Appraisal Waiver Share by Debt-to-Income Ratio (2 of 2)



DTI = debt-to-income. m = month.

Notes: This figure shows the share of appraisal waivers for Fannie Mae and Freddie Mac for loans with DTI of 35 and lower, 36 through 45, and greater than 45. The dashed line in March 2020 marks the approximate date at which the Enterprises' eligibility criteria were aligned. The date corresponds to the month when a loan's respective MBS pool age is 1 month.

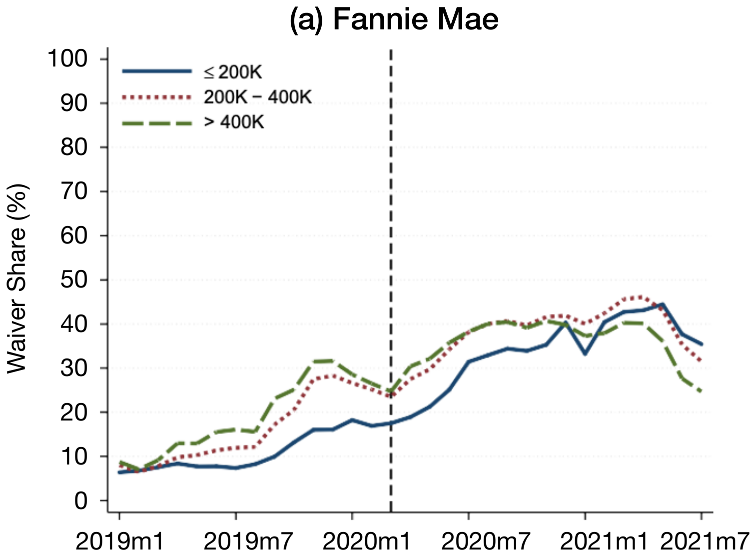
Source: Enterprises' UMBS disclosures accessed via RiskSpan

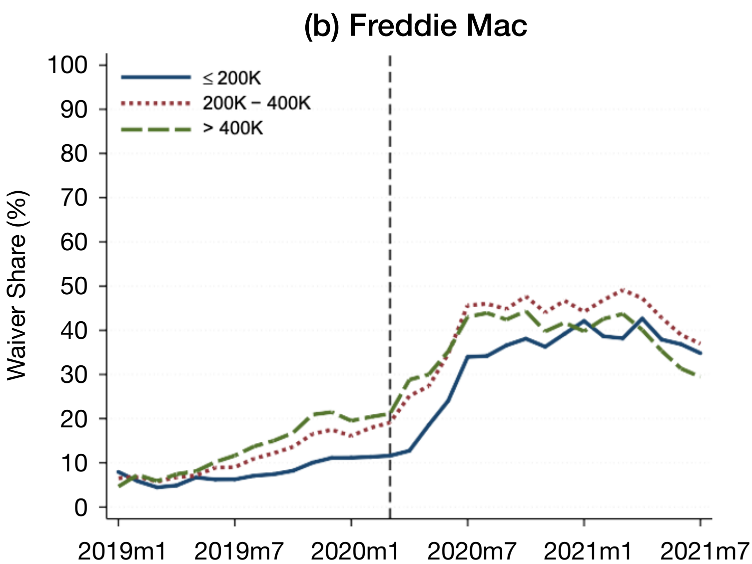
Exhibit A-2 shows that medium-sized loans from $200K through $400K exhibit the highest appraisal waiver shares for both Enterprises, whereas loans for less than $200K have the lowest shares.

Finally, exhibit A-3 shows that, among California, Texas, and Florida, the three largest states in the sample, California has the highest appraisal waiver share, reaching 50 to 60 percent by mid-2020 compared with less than 40 percent for the other two states.

Exhibit A-2

Appraisal Waiver Share by Loan Size





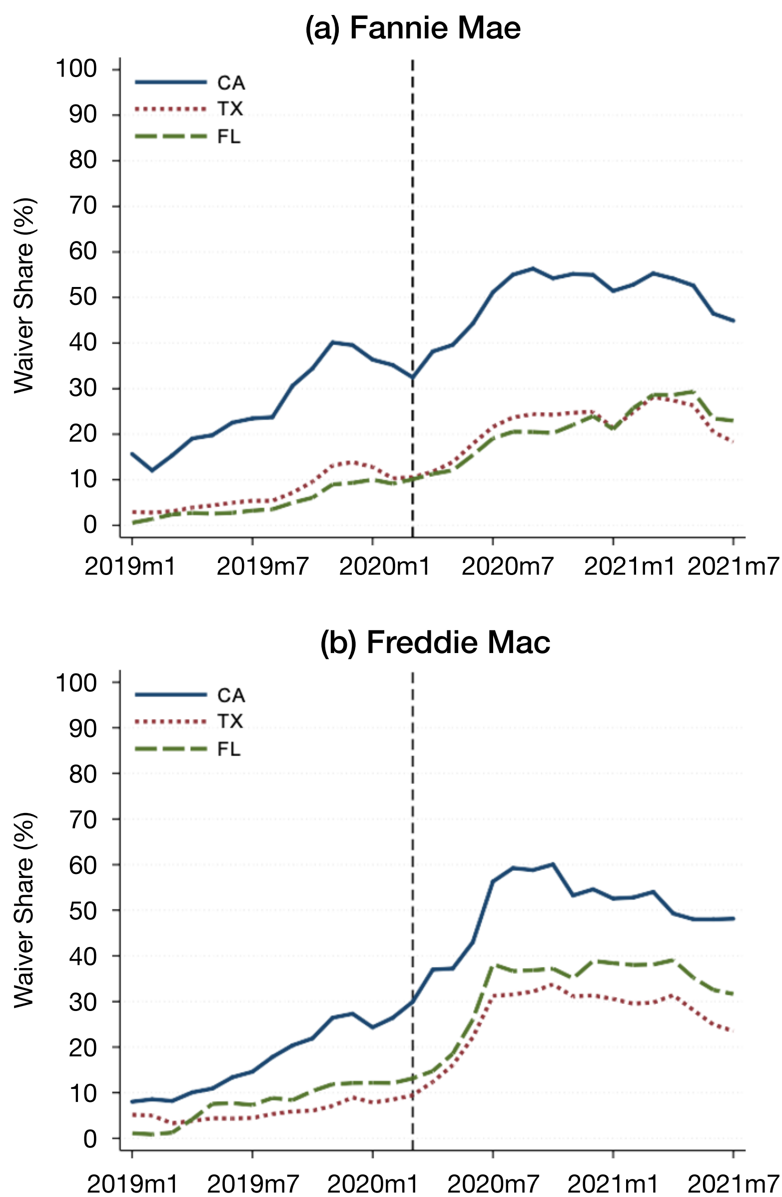
m = month.

Notes: This exhibit shows the share of appraisal waivers for Fannie Mae and Freddie Mac for loans with less than $200,000, between $200,000 and $400,000, and greater than $400,000. The dashed line in March 2020 marks the approximate date at which the Enterprises' eligibility criteria were aligned. The date corresponds to the month when a loan's respective MBS pool age is 1 month.

Source: Enterprises' UMBS disclosures accessed via RiskSpan

Exhibit A-3

Appraisal Waiver Share for Selected Large States



m = month.

Notes: This exhibit shows the share of appraisal waivers for Fannie Mae and Freddie Mac for loans in California, Texas, and Florida. The dashed line in March 2020 marks the approximate date at which the Enterprises' eligibility criteria were aligned. The date corresponds to the month when a loan's respective MBS pool age is 1 month.

Source: Enterprises' UMBS disclosures accessed via RiskSpan

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Applying Seasonal Adjustments to Housing Markets

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The analysis and conclusions are those of the authors alone and should not be represented or interpreted as conveying an official position, policy, analysis, opinion, or endorsement of either the Federal Housing Finance Agency or the U.S. government. Any errors or omissions are the sole responsibility of the authors.

Abstract

House price seasonality has been increasing over the last decade, but adjustments have remained largely unchanged in commonly used public data. This report shows how seasonal adjustments work—both theoretically and applied to observed transactions—when constructing house price indices (HPIs). In this report, the authors find the seasonality in the housing market is not uniform across geographies. Evidence is provided about where adjustments are more necessary, how often they should be recalculated, and how the weather-related variables, social, and industry characteristics impact differences between adjusted and non-adjusted HPIs. Using the Federal Housing Finance Agency's (FHFA's) entire suite of public indices, the authors update adjustments provided by FHFA and offer new adjustments for more than 400 metropolitan areas and other geographies, which haven't been provided before. They find the difference between previous and updated adjusted indices are relatively small, with slight improvement in recent years.

Introduction

House price seasonality has been increasing over the last decade, and regularly utilized and reported house price indices (HPIs) are known to fluctuate due to seasonal events such as changes in weather, major holidays, and school schedules. Mismeasurement could affect how quickly or intensely public policy responds to housing market issues. Nonetheless, seasonal adjustment terms and processes have remained largely unchanged in commonly used public data. Seasonal adjustment is a statistical technique that attempts to measure and remove the influences of predictable patterns, which allows data users to better understand the changes in housing market conditions. This report contains two parts. At first, the authors show how seasonal adjustments work and recalculate the entire suite of public indices provided by the Federal Housing Finance Agency (FHFA). Then, the authors study how adjusted and non-adjusted HPIs have been impacted by changes in weather, such as temperature ranges, average temperature, and precipitation, for both state and metropolitan statistical area (MSA) levels.[1]

Many studies, such as Reichert (1990), Goodman (1993), Kaplanski and Levy (2012), and Ngai and Tenreyro (2014), have looked at certain factors to explain the housing market seasonality, such as daylight savings, marriages, school holidays, interest rates, and climate change. Granger (1978) discusses at least four classes of causes of seasonal fluctuations in economic data, including calendar, timing decisions, weather, and expectation. The changes in weather-related variables might have indirect or direct effects on moves: parents of school-age children have specific reasons for moving during the summer break of school, and marriages peak in the early summer, which influences the moving decisions for those newly married couples (Goodman, 1993). However, G. Miller et al. (2013) use the house price data at the Core Based Statistical Area (CBSA) level to study the seasonality components and find that the temperature variables do not significantly affect the seasonality in the house price. This report will look closely at weather-related variables, which could help explain the seasonality in house prices. Unlike the definition of the range of temperature in G. Miller et al. (2013), who use the average summer temperature minus the average winter temperature, this report utilizes the difference between the minimum temperature and maximum temperature for every quarter. Defining temperature by its range each quarter allows for weather effects to capture larger shifts, which uncovers the impact of the extreme hot or cold seasons on seasonality. Perhaps not surprisingly, the range of temperature is significant and different across quarters. Compared with the impact of the range temperature in Q4, extreme cold winter (with a larger range of temperature in Q1) and extreme hot summer (with a larger range of temperature in Q3) increase the seasonality because it is less pleasant for homebuyers and sellers to engage in market transactions.

Several methods have been used to explore the seasonality in the housing market. The study by Ngai and Tenreyro (2014) uses a search-and-matching model with thick-market effects to study hot and cold seasons of the housing market in the United States and the United Kingdom from 1991 to 2007. Harding et al. (2003) use the hedonic price model to identify the influence of buyer and seller characteristics on bargaining power. G. Miller et al. (2013) use linear regression, with the dependent variable being the variation in seasonality in the CBSAs as measured by standard deviation. This report takes a different route by addressing the actual seasonally adjusted terms.[2] This alternative methodology is conducted in two steps: demonstrate the seasonal adjustments are computed correctly and show whether the changes matter. In the first step, the challenge is that program versions have changed and newer data are available. To isolate the moving parts, a replication is done for the prior program results with prior data before switching to the newer program with prior data and, ultimately, using the newer program on newer data. This switching

[1] MSAs are based on delineations by the Office of Management and Budget (OMB) as of March 2020 in OMB Bulletin No. 20– 01. The file can be accessed at https://www.whitehouse.gov/wp-content/uploads/2020/03/Bulletin-20-01.pdf.

[2] To be fair, other studies have not had the advantage of accessing the entire databases used to create public measures.

involves X-13ARIMA-SEATS (X-13), a seasonal adjustment program that merges X-12-ARIMA (X-12) and the seasonal adjustment module of the TRAMO-SEATS program (Gómez and Maravall, 1996), to make the seasonal adjustment. The difference between previous and updated adjusted indices is relatively small, but with slight improvement in recent years. In the second step of the methodology, seasonality in the housing market is shown not to be uniform across geographies. To study where adjustments are more necessary, a combination of linear and quantile regressions investigate what impacts the difference between a nonseasonally and seasonally adjusted HPI. The results show that the weather-related variables would help to explain the difference, and the effects are larger in the higher seasonality level areas than in the lower seasonality level areas.

The remainder of this report is organized as follows. The next section discusses the data and methodology adopted, followed by the empirical results and robustness tests. In the last section, the conclusion reflects on the implications of adjusting more frequently for seasonality and how that choice is complicated by the large housing market changes during the COVID-19 pandemic.

Data and Methodology

The core focus of this study is to test whether or not there is seasonality in home prices. The technical methodology has two steps. At first, attention is given to the programs used for seasonal adjustment, X-12 and X-13, to show how optimal terms are calculated and applied. After that, a new seasonally adjusted HPI is calculated from the first step to determine the absolute value of the difference between the nonseasonally and seasonally adjusted HPI as the dependent variable in the second step. Moreover, linear regression and quantile regressions try to uncover what might impact the seasonality.

Step 1: Seasonal Adjustment

Cyclical price adjustments can be diagnosed and corrected with automated statistical routines. Seasonal adjustment is easily demonstrated with standard simulations but is less straightforward when multiple data-generating methods are combined. The optimal choice is seldom unique and is sensitive to choices such as sequence lengths and whether outliers are downweighted. When transitioning from simulated to actual data, the challenge becomes even tougher to recalculate cyclical price adjustments for public repeat-sales indices that vary in sales transaction samples and geographic coverage. Below is a demonstration of how seasonal adjustments work theoretically and on actual data by using X-13. The appendix provides more detailed exercises about how the program and options were calibrated with simulated data.

X-13ARIMA-SEATS Routine

FHFA has used the X-12 routine in the past, and the X-12 software is one of the most popular methods for seasonal adjustment; however, the software functionality has since been upgraded to X-13, which is downloadable from the Census Bureau. X-13 merges with the version of X-12 and SEATS. The version of X-12 used in X-13 is version 0.3, and a crucial new feature of Version 0.3 of X-12 is an updated automatic AutoRegressive Integrated Moving Average (ARIMA) model identification procedure, based on Gómez and Maravall (1996). Three stages are needed to complete the seasonal adjustment: model building, seasonal adjustment, and diagnostic checking. In the first stage, regARIMA performs prior adjustments for various effects, such as trading-day effects, moving holiday effects, and outliers. In the second stage, X-12 estimates its parameters by maximum likelihood using an iterated generalized least-squares algorithm. The third stage is diagnostic checking, examining the residuals from the fitted model, including outlier detection, normality test, and the Ljung-Box Q test.

To present the general regression for a regARIMA model, a formula is used similar to in Wang and Wu (2012), and it can be written as

$$\phi(B)\Phi(B^s)(1-B^s)^D(y_t - \sum_{i=1} \beta_i x_{it}) = \theta(B)\Theta(B^s)\epsilon_t, \tag{1}$$

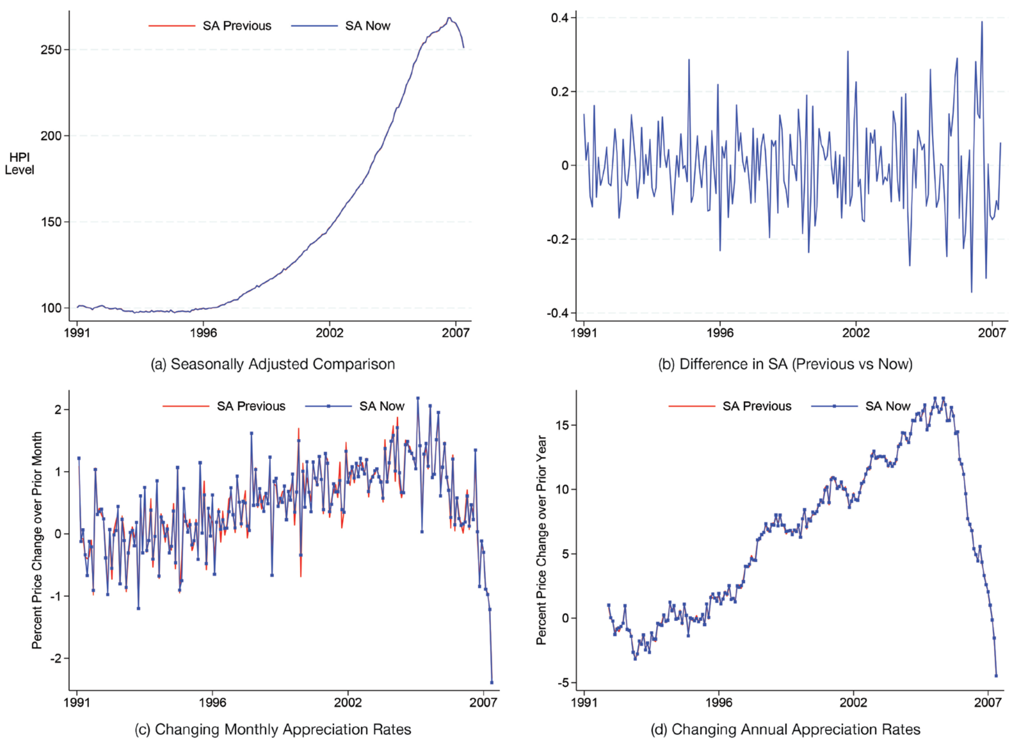
where y_t is the dependent variable to be adjusted; B is the lag operator $By_t = y_{t-1}$; s denotes the seasonal period; $\phi(B) = 1 - \phi_1 B - \ldots - \phi_p B^p$ denotes the regular autoregressive operator; $\Phi(B^s) = 1 - \Phi_1 B^s - \ldots - \Phi_P B^{Ps}$ denotes the seasonal autoregressive operator; $\theta(B) = 1 - \theta_1 B - \ldots - \theta_q B^q$ denotes the regular moving average operator; $\Theta(B^s) = 1 - \Theta_1 B - \ldots - \Theta_Q B^{Qs}$ denotes the seasonal moving average operator; and the ϵ_t are independent and identically distributed with mean 0 and variance σ^2.

Seasonality in Housing Markets

The seasonally adjusted term structures are updated in two steps. First, it is necessary to show what happens to the seasonally adjusted HPI when switching from one program (X-12) to a new version (X-13) but while retaining the original optimal term structure. Exhibit 1 compares the prior seasonally adjusted HPIs performed by X-12 and the new seasonally adjusted HPIs done by X-13. The adjusted indices are extremely similar. The results show that the lines of previous and current seasonally adjusted house prices, monthly appreciation rates, and annual appreciation rates are overlapping, and the difference between them is very small (almost visually not noticeable) across the panels.

Exhibit 1

SA Terms after Switching from X-12 to X-13



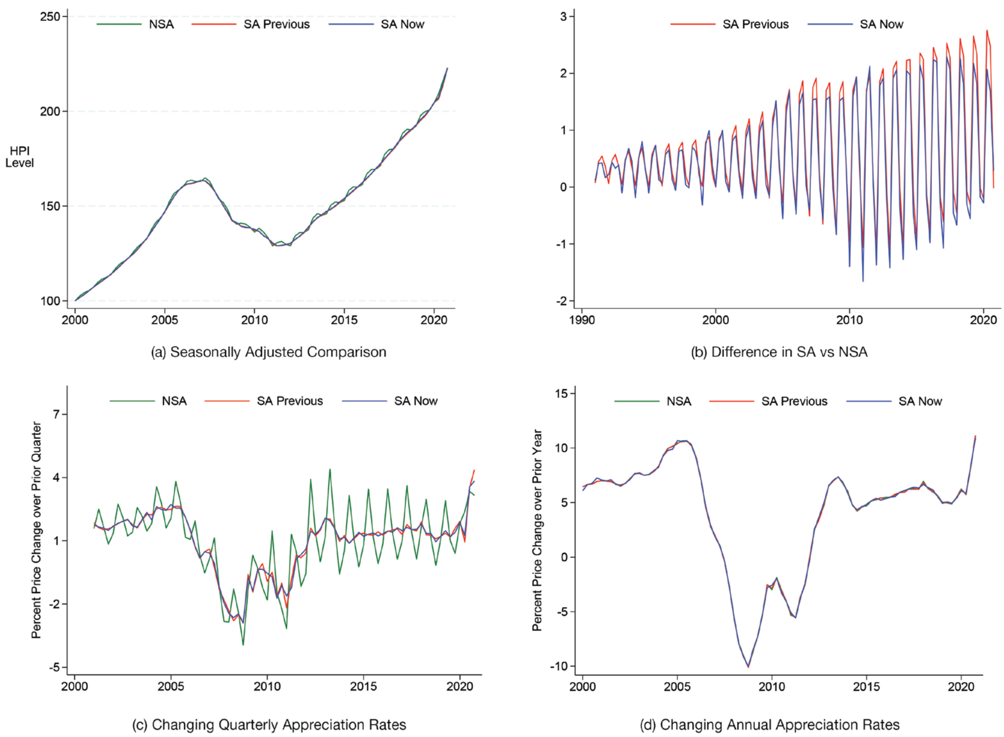
Sources: House values are from single-family mortgages either purchased or securitized by Fannie Mae or Freddie Mac

Second, the optimal parameters are recomputed with newer data, and those newly adjusted indices are compared to the entire suite of public indices provided by FHFA.[3] Exhibit 2 also illustrates the differences with the new HPIs are relatively minor, but the newly adjusted indices (labeled as "now") have a slightly tighter range when computing differences with the suite of public indices (labeled as "previous").

[3] As noted later, the exercise extends slightly further by offering adjustments that have not been provided for 400 MSAs and other geographies. Previously, ARIMA routines were not run regularly because of computational challenges, but these have largely been overcome as shown in the appendix, which lists the approximate production times as estimated by each type of index and geography.

Exhibit 2

Computing New Optimal SA Terms

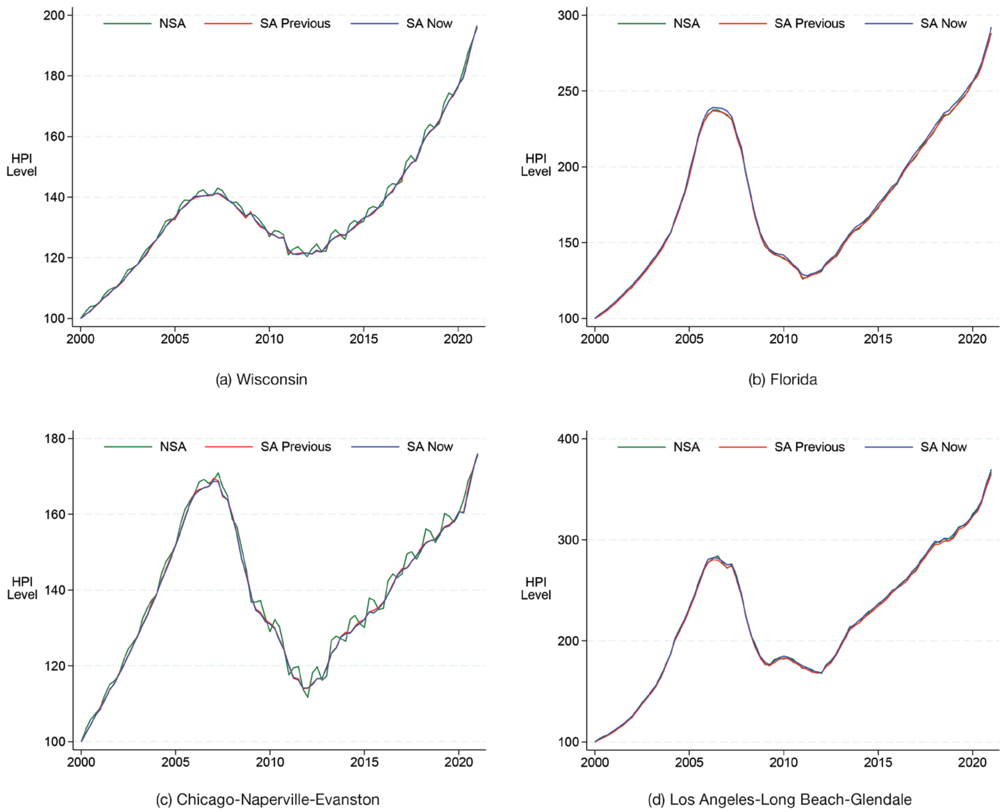


Sources: House values are from single-family mortgages either purchased or securitized by Fannie Mae or Freddie Mac

Next, evidence is provided about where adjustments are more necessary; in other words, the seasonality in the housing market is not uniform across areas. In exhibit 3, seasonal adjustments are compared between two states and two MSAs. Looking across the top row, there is a larger difference between the nonseasonally and seasonally adjusted house price index, which is larger in Wisconsin than in Florida. The same result happens when comparing among MSAs; a seasonal adjustment in Chicago-Naperville-Evanston is more necessary than in Los Angeles-Long Beach-Glendale.

Exhibit 3

Seasonally Adjusted Comparison between Two States and Two MSAs



Sources: House values are from single-family mortgages either purchased or securitized by Fannie Mae or Freddie Mac

Forecast

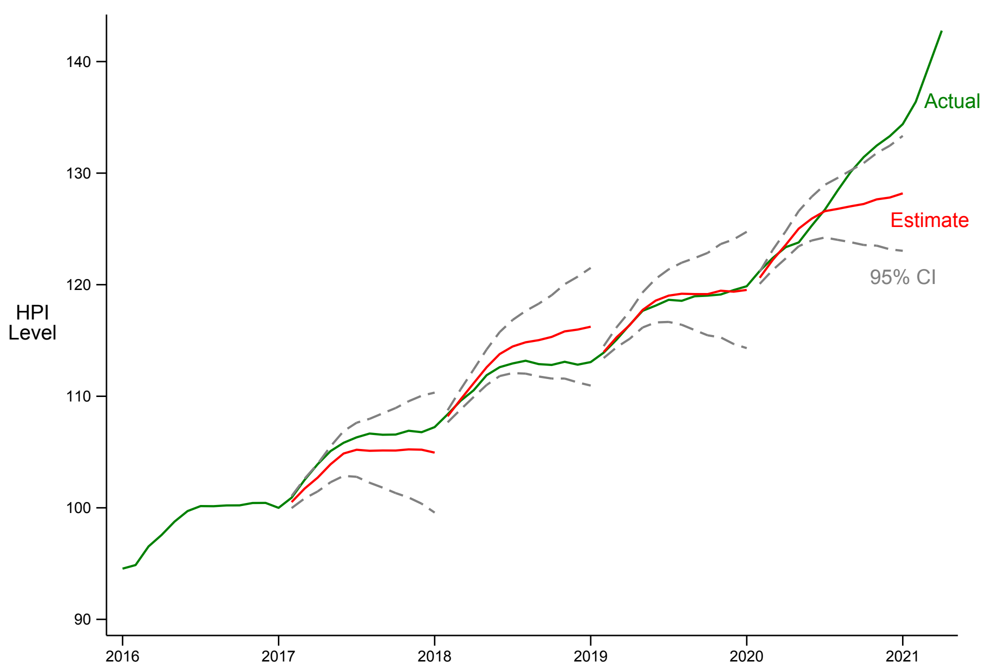
A reasonable question is whether the newly adjusted indices provide more accurate gauges for how housing markets might perform in future periods. The exercise is particularly relevant with modeling the COVID-19 era because it is not clear whether the last several years have been transitory and should be treated as an outlier event or if the pandemic has made a permanent impression on housing markets that will require new seasonally adjusted terms for proper measurement.

Several reports analyze seasonal adjustments during COVID-19 and make comparisons among different seasonally adjusted methods. Bógalo et al. (2022) compares X-13 with newly introduced nonparametric Circulant Singular Spectrum Analysis (CiSSA) in COVID-19 times and find that X-13 with outlier detection seems a better option. For outlier options in X-13, Tiller et al. (2021) explore various options for automatic outlier selections during the pandemic using unemployment series in 421 metro areas, and they find that LSs in combination with TCs and AOs provides the best fit overall. Abeln and Jacobs (2021), on the other hand, compare X-13 with CAMPLET before and after the COVID-19 pandemic of the quarterly series real GDP, and they find that differences in SA values are generally small.

In this report, X-13 is used to forecast the following year's price index. As shown in exhibit 4, the forecasting performs very well during 2017, 2018, and especially 2019. For 2020, March is approximately when house prices started derailing due to COVID-19. House prices have risen substantially since the COVID-19 pandemic; the annual gains are two to three times greater than before. Will house prices keep increasing or revert back? Given this context, determining the optimal seasonal adjustment for housing prices has become a difficult task. Two main options stand out depending on the future trend of housing prices: use concurrent seasonal adjustment with outlier commands in X-13 if the housing markets revert back (Bógalo et al., 2022; Tiller et al., 2021), or establish a structural break and estimate new optimized terms if the house prices keep increasing at a higher rate.

Exhibit 4

Forecasting House Prices at the Start of Each Year



Sources: House values are from single-family mortgages either purchased or securitized by Fannie Mae or Freddie Mac. Estimates are calculated by the X-13 routine as of each January

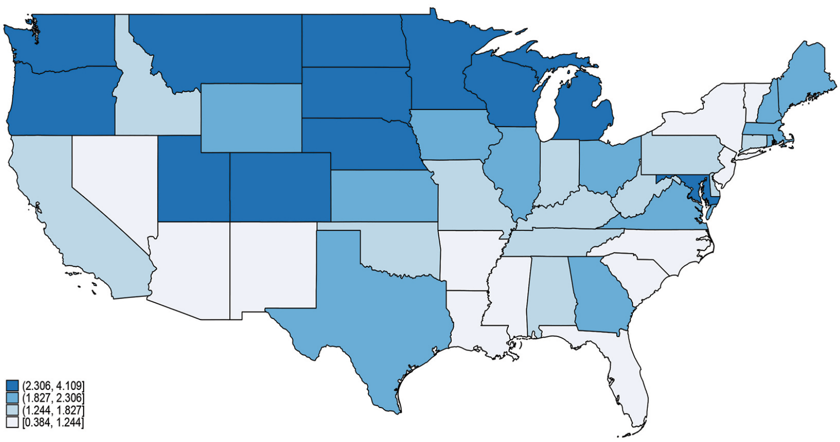
Step 2: Causation of the Seasonality

The prior step has shown that there is seasonality in home prices, and the seasonality is not uniform across areas. The remaining question is: What may lead to the different seasonality in housing markets across states and MSAs, and where are adjustments more necessary? The absolute value of the difference between the nonseasonally adjusted and seasonally adjusted house prices is used as a measurement of seasonality. Adjustments are more necessary when there are larger absolute values of the difference.

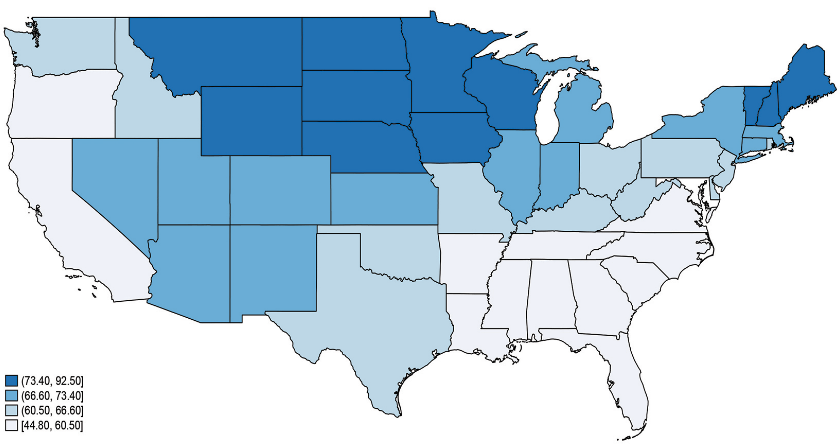
The actual causation of seasonality in housing prices may be due to a complicated mix of many factors, which might directly or indirectly impact the housing market. Actual changes in temperature, average temperature, and rainfall have direct effects on various economic time series, such as those concerned with agricultural production, construction, and transportation, and consequent indirect effects on housing prices. Exhibit 5 shows the absolute value of the difference between the nonseasonally and seasonally adjusted house price index. In the top panel, HPI differences are larger in states with a darker shade. The bottom panel shows the range of temperatures, which is defined as the difference between the maximum and minimum temperatures. Comparing the two exhibits, it is clear that the distribution of colors is very close, and the greater range of temperatures is likely correlated with increased seasonality in house prices.

Exhibit 5

Geographic Similarities of HPI Seasonality and Weather Data



(a) Difference between NSA and SA HPI Values



(b) Range of Temperatures

Sources: House values are from single-family mortgages either purchased or securitized by Fannie Mae or Freddie Mac. Weather information is obtained from the National Oceanic and Atmospheric Administration

Two different empirical methods, linear regression and quantile regression, examine the differences in NSA and SA terms on weather-related variables, social and industry characteristics, and temporal and geographic controls. The data and specifications are explained below.

Data

The HPI data used in the regression are the public-use quarterly data from 1991 to 2020 for both state and MSA levels from FHFA. Weather data are obtained from the National Oceanic and Atmospheric Administration (NOAA). Moreover, demographic data on household and industry variables come from census data in 2010.

Linear and Quantile Regression

Some studies (e.g., Goodman, 1993; Kaplanski and Levy, 2012) have looked at certain factors to explain seasonality, such as daylight savings, marriages, summer relocations, school holidays, etc. This report runs regression to test other factors, with the dependent variable being the absolute value of the difference between the seasonally and nonseasonally adjusted HPI in both state and MSA levels:

$$y_{it} = \alpha + \beta_1 W_{it} + \beta_2 N.sales_{it} + \beta_3 Char_{i,2010} + \beta_4 Industry_{i,2010} + \gamma_i + f(year) + \epsilon_{it} \quad (2)$$

Unlike the linear regression model, based on the conditional mean of the dependent variable, quantile regression is based on the conditional τ^{th} quantile of the dependent variable. Quantile regressions uncover the hidden seasonality factors that exist depending on the relatively distributional level of seasonality. The quantile regression for the τ^{th} quantile is

$$Q_\tau(y_{it}) = \alpha_\tau + \beta_{1\tau} W_{it} + \beta_{2\tau} N.sales_{it} + \beta_{3\tau} Char_{i,2010} + \beta_{4\tau} Industry_{i,2010} + \gamma_{i\tau} + f_\tau(year) + \epsilon_{it} \quad (3)$$

where y_{it} is the absolute value of the difference between nonseasonally adjusted and seasonally adjusted (from step one) house price index for i^{th} State/MSA at each quarter; W_{it} weather-related variables included the range of temperature, average temperature, and precipitation. Unlike the definition of the range of temperature in G. Miller et al. (2013), they define it as the difference between the average summer temperature and the average winter temperature; here the difference is measured between the minimum temperature and maximum temperature for every quarter. $N.sales_{it}$ is the average number of houses sold in each quarter. $Char_{i,2010}$ contains the characteristic of the population in the area: average household income, the percentage of white, the percentage of the population older than 65 years old, the percentage of the population with the education of bachelor's or higher, and the percentage of single-family sales. $Industry_{i,2010}$ includes the percentage share of the top 10 industries in the i^{th} State/MSA. Also, γ_i is State/MSA fixed effect. $f(year)$ is linear splines for years, which allow estimating the relationship between seasonality and year as a piecewise linear function. ϵ_{it} is the error term, which is assumed to be normally distributed.

Results

Exhibit 6 summarizes the results for the linear regression analysis.[4] Throughout the table, the dependent variable, the difference between nonseasonally and seasonally adjusted HPI, is regressed on weather-related variables, social and industry characteristics, and temporal and geographic controls.

Exhibit 6

The Impact of Seasonality on House Price Measures

Estimate	State					MSA				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 1	Model 2	Model 3	Model 4	Model 5
Weather										
Range Temp Q1	0.014*** (11.58)	0.017*** (13.46)	0.015*** (15.59)	0.016*** (11.00)	0.011*** (9.93)	0.018*** (18.69)	0.017*** (18.60)	0.018*** (23.29)	0.016*** (17.45)	0.018*** (23.80)
Range Temp Q2	0.010*** (10.28)	0.006*** (4.66)	0.008*** (7.84)	0.005*** (3.27)	0.014*** (10.25)	0.005*** (5.45)	0.006*** (6.56)	0.005*** (6.92)	0.008*** (9.28)	0.006*** (7.45)
Range Temp Q3	0.020*** (12.92)	0.011*** (5.13)	0.016*** (9.38)	0.009*** (2.91)	0.027*** (11.14)	0.006*** (5.87)	0.006*** (6.97)	0.006*** (7.44)	0.008*** (9.38)	0.006*** (7.92)
Range Temp	– 0.018*** (– 7.78)	– 0.014*** (– 5.95)	– 0.016*** (– 8.36)	– 0.013*** (– 5.29)	– 0.018*** (– 9.04)	– 0.003** (– 2.01)	– 0.001 (– 0 .57)	– 0.004*** (– 3.15)	– 0.004** (– 2.41)	– 0.005*** (– 3.41)
Average Temp	– 0.017*** (– 11.73)	– 0 .003 (– 1.30)	– 0.011*** (– 6.26)	0.003 (0.93)	– 0.025*** (– 8.78)	– 0.003*** (– 3.33)	0.002** (2.47)	0.001 (1.02)	0.003*** (3.77)	0.001* (1.94)
Precipitation	– 0.032*** (– 3.36)	– 0 .014 (– 1.31)	– 0.018** (– 2.14)	– 0.006 (– 0.54)	– 0.013 (– 1.48)	– 0.010** (– 2.25)	– 0.014*** (– 3.02)	– 0.021*** (– 5.38)	– 0.000 (– 0.07)	– 0.004 (– 0.95)
ln (Number of Sales)		– 0.192*** (– 9.27)	0.044** (2.43)	– 0.609*** (– 19.05)	0.004 (0.11)		– 0.182*** (– 12.86)	– 0.035*** (– 2.93)	– 0.605*** (– 23.43)	– 0.084*** (– 3.57)
Year Spline										
Year [1991,1998]			0.023*** (3.85)		0.027*** (4.48)			0.020*** (3.76)		0.021*** (4.08)
Year [1999,2007]			0.100*** (21.20)		0.099*** (21.06)			0.127*** (29.78)		0.126*** (30.54)
Year [2008,2011]			0.107*** (9.69)		0.103*** (9.03)			0.075*** (7.69)		0.071*** (7.34)
Year [2012,2020]			– 0.009 (– 1.37)		– 0.006 (– 0.88)			0.014** (2.34)		0.015*** (2.68)
Household Characteristics		Y	Y	Y	Y		Y	Y	Y	Y
Industry Concentration Shares		Y	Y	Y	Y		Y	Y	Y	Y
Fixed Effect				State	State				MSA	MSA
Goodness of Fit										
R^2	0.099	0.171	0.467	0.231	0.494	0.034	0.111	0.389	0.185	0.438
BIC	16,835	16,465	13,847	16,322	13,842	38,684	37,832	33,373	37,579	33,177
N	6,000	6,000	6,000	6,000	6,000	11,963	11,963	11,963	11,963	11,963

*Notes: The difference between NSA HPI and SA HPI is models as a function of weather-related variables, social and industry characteristics, and temporal and geographic controls. Quarterly frequency. Range Temp is defined as the difference between the maximum and minimum temperature. Hawaii is not included because of missing data on weather. Industries are ordered based on popularity, and the 10 most popular industries are listed. Top 100 MSA are included in the models. N is calculated by the number of State/MSA×120. t-value in parentheses. * for p < .1, ** for p < .05, and *** for p < .01.*

Sources: House values are from single-family mortgages either purchased or securitized by Fannie Mae or Freddie Mac. Weather information is obtained from the National Oceanic and Atmospheric Administration. Household demographics and industry characteristics are from the United States Census Bureau

[4] The full table is presented in the appendix (exhibit A-9).

In model 1, the outcome of interest is regressed against weather controls—range of temperature, average temperature, and precipitation. While controlling only for weather, the findings show that 9.9 percent of HPI seasonality can be explained by weather controls at the State level, and only 3.4 percent in the MSA level. Then, in model 2, controls are added for household characteristics and industry concentration shares. The presence of contemporaneous controls has no large impact on the estimates for weather controls. In model 3, a linear spline is used for a variable year, which allows estimating the relationship between the seasonality of HPI and year as a piecewise linear function; in other words, the average growth rate of the difference between a nonseasonally and seasonally adjusted HPI can be different at different periods of time. Estimates show that the seasonality increases slowly over time from 1991 to 1998; the seasonality increases at a higher rate from 1999 to 2011; the increasing rate of seasonality slows down from 2012 to 2020.

Then for model 4, instead of controlling for time trends, State/MSA fixed effects are included. Model 5 allows for both time trends and State/MSA fixed effect. After adding the controls for all variables (model 5), the R-squared increases from 0.099 to 0.494 for State level and goes up from 0.034 to 0.438 for MSA level. This gain in model fit does not mean the geographic fixed effects are the most important contribution, though, because a comparison between models 3 and 5 suggests that the time trends capture a greater share of the explained variation in classical linear regression. Generally, the regression results for the temperature variables are significant and have consistent patterns among models. Model 5 shows that an increase of one degree for the range of temperature in Q4 reduces the difference between nonseasonally and seasonally adjusted HPI on average by 1.55 percent for State level and only 0.39 percent for MSA.[5] Compared with Q4: a one-degree increase in the range of temperature in Q1 increases the seasonality on average by about 0.95 percent for the State level and about 1.40 percent for the MSA level; a one-degree increase in the range of temperature in Q2 increases the seasonality on average by about 1.21 percent for State level and about 0.47 percent for MSA level; one degree increased in the range of temperature in Q3 increases the seasonality on average by about 2.33 percent in the State level and 0.47 percent in the MSA level. The results for the range of temperature show extreme cold winter (larger range of temperature in Q1) would increase the seasonality of HPI in the MSA level, and extreme hot summer (larger range of temperature in Q3) would increase the seasonality of HPI in the State level.

Along with the linear regression results, estimates of the 10th, 25th, 50th, 75th, and 90th quantiles are provided to demonstrate the effects of the explanatory variables at each quantile. The results for quantile regression are shown in exhibit 7.[6] Unlike linear regression, quantile regression allows the impact of a specific variable to be distinguished according to the dependent variable threshold. The range of temperature in Q4 has a significant adverse effect on the seasonality, and the pattern of the quantile parameters shows an increasing trend of this negative effect at the State and MSA levels. For Q1 and Q3, the pattern of quantile parameters shows an increasing trend of this positive effect in both State and MSA levels. Extreme hot summer and extreme cold winter aggravate the seasonality of HPI for places with higher seasonality levels. However, for Q2, the quantile regression reveals that the parameter reaches the maximum point at the center of the distribution for both State and MSA levels. The quantile regression provides additional information that the impact of the range temperature is different across quantiles. For the impact of year trend, in general, the seasonality increases over time, and the quantile

[5] The average of the difference between the nonseasonally and seasonally adjusted HPI is 1.158 in State level and 1.290 in MSA level. We calculate 0.011/1.158 = 1.55 percent and 0.005/1.290 = 0.39 percent.

[6] The full table of quantile regression is presented in the appendix (exhibit A-10).

parameters show an increasing trend from 1991 to 2011. However, the story is different from 2012 to 2020: the seasonality has been reduced for places with lower seasonality levels (10th, 25th, and 50th quantiles); the seasonality does not change for states with the higher seasonality level; the seasonality increases for MSAs in the 90th quantile.

Exhibit 7

Splitting up Seasonality by Quantile

Estimate	State					MSA				
	0.1	0.25	0.5	0.75	0.9	0.1	0.25	0.5	0.75	0.9
Weather										
Range Temp Q1	0.005*** (3.89)	0.011*** (11.74)	0.015*** (14.05)	0.018*** (13.40)	0.019*** (10.39)	0.006*** (8.98)	0.012*** (15.78)	0.017*** (21.92)	0.022*** (19.95)	0.024*** (15.75)
Range Temp Q2	0.004*** (3.33)	0.006*** (6.29)	0.007*** (6.06)	0.006*** (4.61)	0.004** (2.18)	0.002*** (3.03)	0.003*** (4.72)	0.003*** (3.96)	0.002* (1.65)	0.001 (0.75)
Range Temp Q3	0.007*** (3.52)	0.011*** (7.13)	0.015*** (8.11)	0.018*** (7.99)	0.015*** (4.78)	0.003*** (5.17)	0.006*** (7.66)	0.006*** (8.04)	0.006*** (5.49)	0.007*** (4.37)
Range Temp	– 0.005** (– 2.18)	– 0.009*** (– 5.03)	– 0.010*** (– 4.85)	– 0.010*** (– 3.98)	– 0.014*** (– 4.06)	– 0.001 (– 0.52)	– 0.004*** (– 3.19)	– 0.004*** (– 3.04)	– 0.003* (– 1.81)	– 0.005** (– 2.18)
Average	– 0.005** (– 2.23)	– 0.007*** (– 3.82)	– 0.011*** (– 5.24)	– 0.014*** (– 5.74)	– 0.012*** (– 3.48)	– 0.000 (– 0.10)	– 0.001 (– 0.97)	– 0.001 (– 0.91)	0.001 (0.85)	0.002 (1.46)
Precipitation	– 0.004 (– 0.43)	– 0.005 (– 0.60)	– 0.006 (– 0.61)	– 0.007 (– 0.63)	– 0.008 (– 0.50)	– 0.001 (– 0.33)	– 0.005 (– 1.35)	– 0.008** (– 2.03)	– 0.020*** (– 3.73)	– 0.038*** (– 5.06)
ln (Number of Sales)	0.046** (2.15)	0.078*** (4.51)	0.053*** (2.67)	0.013 (0.52)	– 0.059* (– 1.76)	0.018* (1.77)	0.036*** (3.11)	0.007 (0.61)	– 0.052*** (– 3.06)	– 0.136*** (– 5.83)
Year Spline										
Year [1991,1998]	0.015** (2.10)	0.018*** (3.11)	0.020*** (3.08)	0.019** (2.33)	0.026** (2.39)	0.009** (2.03)	0.015*** (2.93)	0.018*** (3.49)	0.016** (2.11)	0.018* (1.75)
Year [1999,2007]	0.028*** (5.03)	0.064*** (14.19)	0.091*** (17.43)	0.119*** (18.24)	0.132*** (14.89)	0.028*** (8.01)	0.069*** (17.03)	0.117*** (27.27)	0.165*** (27.28)	0.207*** (25.09)
Year [2008,2011]	0.049*** (3.75)	0.076*** (7.22)	0.119*** (9.79)	0.144*** (9.46)	0.183*** (8.85)	0.041*** (5.04)	0.072*** (7.73)	0.087*** (8.83)	0.103*** (7.40)	0.098*** (5.16)
Year [2012,2020]	– 0.016** (– 2.08)	– 0.019*** (– 3.08)	– 0.019*** (– 2.65)	– 0.011 (– 1.26)	0.005 (0.37)	– 0.020*** (– 4.14)	– 0.031*** (– 5.61)	– 0.014** (– 2.42)	0.008 (0.92)	0.061** (5.47)
Controls										
Household Characteristics	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry Shares	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Goodness of Fit										
R^2	0.092	0.199	0.312	0.387	0.438	0.064	0.149	0.260	0.332	0.373
N	6,000	6,000	6,000	6,000	6,000	11,963	11,963	11,963	11,963	11,963

*Notes: The difference between NSA HPI and SA HPI is models as a function of weather-related variables, social and industry characteristics, and temporal and geographic controls. Quarterly frequency. Range Temp is defined as the difference between the maximum and minimum temperature. Hawaii is not included because of missing data on weather. Industries are ordered based on popularity, and the 10 most popular industries are listed. Top 100 MSA are included in the models. N is calculated by the number of State/MSA×120. t-value in parentheses. * for p < .1, ** for p < .05, and *** for p < .01.*

Sources: House values are from single-family mortgages either purchased or securitized by Fannie Mae or Freddie Mac. Weather information is obtained from the National Oceanic and Atmospheric Administration. Household demographics and industry characteristics are from the United States Census Bureau

To explain the empirical patterns, this report uses the magnitude of the difference between the nonseasonally and seasonally adjusted HPI as the variation in seasonality. Two major factors affect the seasonality: weather controls and time trends. Throughout models, the impacts of temperature variables are significant and different across quarters, and the coefficients for weather-related variables remain fairly constant. Comparing with the weather controls, time trends are a much stronger driver. Additionally, the quantile regression indicates that the pattern of the quantile parameters generally shows an increasing trend for temperature variables. Although many reports have discovered that house price seasonality has increased over time, the findings in this report offer a nuance that seasonal impacts have persisted for well over the past 30 years. However, the patterns are different—seasonality rose slowly from 1991 to 1998, increased fast from 1999 to 2011, and slowed down in recent years.

Robustness Tests

These results indicate that the weather-related variables had a significant impact on the difference between adjusted and non-adjusted HPI. Four sensitivity exercises help test specifications for the analysis.

In the first robustness check, the original model is reestimated (model 5) conditional on the time between sales to examine whether the conclusions change. The HPI data used are repeat-sales data[7] from FHFA. Moreover, the change in the transaction prices is found to be a function of the time between sales based on the assumption that the vectors of physical and location characteristics do not change over time in repeat-sales data. To test for sensitivity, the sample selection criteria is based on the time between sales. In exhibit 8,[8] the estimates for subsamples are separated by the time between sales—"Short Time," "Average Time," and "Long Time." "Short Time" is defined for those MSAs or States whose average time between sales is in the lower 33 percent among the top 100 MSAs or States; "Average Time" is between 34 and 66 percent; "Long Time" is higher than 67 percent. The estimated sign is consistent, and the pattern of effects is similar across these columns. In addition, weather controls provide the larger improvement for the MSAs or States with longer average time between sales, but the estimated effects remain similar to the main findings.

Exhibit 8

Stratifying Seasonality by Time-between-Sales (1 of 2)

Estimate	State			MSA		
	Short Time	Average Time	Long Time	Short Time	Average Time	Long Time
Weather						
Range Temp Q1	0.010*** (5.13)	0.011*** (6.44)	0.014*** (5.89)	0.011*** (10.19)	0.022*** (19.43)	0.022*** (13.56)
Range Temp Q2	0.010*** (4.30)	0.012*** (5.58)	0.018*** (7.58)	0.002 (1.48)	0.007*** (5.94)	0.009*** (5.58)
Range Temp Q3	0.025*** (5.83)	0.019*** (4.95)	0.038*** (8.11)	– 0.001 (– 0.95)	0.011*** (9.63)	0.009*** (5.62)
Range Temp	– 0.017*** (– 5.46)	– 0.013*** (– 3.76)	– 0.023*** (– 6.31)	0.001 (0.56)	– 0.009*** (– 4.01)	– 0.009*** (– 2.86)
Average	– 0.023*** (– 4.35)	– 0.021*** (– 4.38)	– 0.035*** (– 6.47)	0.003** (2.42)	0.001 (0.86)	– 0.000 (– 0.01)
Precipitation	– 0.027* (– 1.67)	– 0.025 (– 1.40)	0.010 (0.73)	– 0.004 (– 0.54)	0.005 (0.59)	– 0.007 (– 1.11)

[7] The repeat-sales methodology is introduced in the appendix.

[8] The full table is presented in the appendix (exhibit A-11).

Exhibit 8

Stratifying Seasonality by Time-between-Sales (2 of 2)

Estimate	State			MSA		
	Short Time	Average Time	Long Time	Short Time	Average Time	Long Time
Year Spline						
Year [1991,1998]	0.030*** (2.85)	0.013 (1.26)	0.023** (2.27)	0.005 (0.55)	0.021*** (2.60)	0.026** (2.54)
Year [1999,2007]	0.074*** (9.48)	0.115*** (13.66)	0.118*** (14.17)	0.121*** (17.13)	0.134*** (20.53)	0.128*** (15.79)
Year [2008,2011]	0.102*** (5.19)	0.127*** (6.41)	0.110*** (5.50)	0.132*** (7.85)	0.029* (1.86)	0.065*** (3.55)
Year [2012,2020]	– 0.007 (– 0.67)	– 0.000 (– 0.04)	– 0.024** (– 2.06)	– 0.007 (– 0.67)	– 0.001 (– 0.15)	0.045*** (4.17)
Controls						
Household Char	Y	Y	Y	Y	Y	Y
Industry Shares	Y	Y	Y	Y	Y	Y
Fixed Effect	MSA	MSA	MSA	MSA	MSA	MSA
Goodness of Fit						
R^2	0.420	0.556	0.521	0.462	0.480	0.406
BIC	4,693	4,334	4,780	10,446	9,973	12,361
N	2,040	1,920	2,040	3,940	3,953	4,070
Num. State/MSA	17	16	17	33	33	34
Percentile	<33%	34%-66%	>67%	<33%	34%-66%	>67%

*Notes: The difference between NSA HPI and SA HPI is models as a function of weather-related variables, social and industry characteristics, and temporal and geographic controls. Quarterly frequency. Range Temp is defined as the difference between the maximum and minimum temperature. Hawaii is not included because of missing data on weather. Short Time cities are defined if the time between sales is in the lower 33 percent among the top 100 MSA; Average cities are between 34 and 66 percent; Long Time cities are higher than 67 percent. N is calculated by the number of State/MSA×120. t-value in parentheses. * for p < .1, ** for p < .05, and *** for p < .01.*

Sources: House values are from single-family mortgages either purchased or securitized by Fannie Mae or Freddie Mac. Weather information is obtained from the National Oceanic and Atmospheric Administration. Household demographics and industry characteristics are from the United States Census Bureau

In the second robustness check, controls are introduced for unobserved effects sensitive to MSA sizes based on MSA population (10th, 25th, 75th, and 90th quantiles). Estimations are rerun for model 5 conditional on different MSA sizes, and the results are shown in exhibit 9.[9] In general, the coefficients of the temperature range are similar for MSAs whose population is between the 10th and 90th quantiles. However, the range of temperature has larger and significant impact on seasonality for extremely large MSAs (higher than 90th quantile) and smaller or insignificant effects for extremely small MSAs (lower than 10th quantile).

[9] The full table is presented in the appendix (exhibit A-12).

Exhibit 9

The Impact of Seasonality by City Size

Estimate	Smallest City	Small City	Medium City	Large City	Largest City
Weather					
Range Temp Q1	0.011*** (4.80)	0.016*** (11.07)	0.017*** (15.01)	0.020*** (10.96)	0.033*** (14.73)
Range Temp Q2	0.002 (0.75)	0.002 (1.16)	0.007*** (6.02)	0.009*** (4.79)	0.007*** (3.22)
Range Temp Q3	0.006*** (2.66)	0.007*** (4.81)	0.004*** (3.10)	0.006*** (3.18)	0.022*** (10.12)
Range Temp	0.005 (1.01)	– 0.007** (– 2.36)	– 0.005** (– 2.20)	– 0.006 (– 1.55)	– 0.014*** (– 3.52)
Average	0.003 (1.57)	– 0.000 (– 0.01)	0.002** (2.19)	0.000 (0.11)	– 0.003 (– 1.64)
Precipitation	0.027* (1.94)	0.011 (0.89)	– 0.018** (– 2.23)	– 0.000 (– 0.10)	– 0.006 (– 0.33)
Year Spline					
Year [1991,1998]	0.026 (1.54)	0.025** (2.41)	0.019** (2.46)	0.027** (2.31)	0.037*** (2.61)
Year [1999,2007]	0.104*** (7.84)	0.090*** (10.66)	0.142*** (22.02)	0.121*** (13.00)	0.104*** (8.57)
Year [2008,2011]	0.024 (0.77)	0.031 (1.54)	0.076*** (5.07)	0.103*** (4.91)	0.078*** (3.06)
Year [2012,2020]	0.053*** (2.83)	0.004 (0.35)	0.038*** (4.31)	– 0.039*** (– 3.14)	– 0.030** (– 2.02)
Controls					
Household Char	Y	Y	Y	Y	Y
Industry Shares	Y	Y	Y	Y	Y
Fixed Effect	MSA	MSA	MSA	MSA	MSA
Goodness of Fit					
R^2	0.411	0.398	0.452	0.471	0.481
BIC	3,269	4,045	18,116	4,495	2,588
N	1,186	1,794	6,109	1,798	1,076
Num. MSA	10	15	51	15	9
Percentile	<10%	10%-25%	25-75%	75%-90%	>90%

*Notes: The difference between NSA HPI and SA HPI is models as a function of weather-related variables, social and industry characteristics, and temporal and geographic controls. Quarterly frequency. Range Temp is defined as the difference between maximum and minimum temperature. Hawaii is not included because of missing data on weather. Tiny cities are defined if the populations are in the lower 10 percent of the top 100 MSA; Small cities are lower 25 percent; Median cities are between 25 and 75 percent; large cities are higher than 75 percent; Huge cities are lower than 90 percent. N is calculated by the number of State/MSA×120. t-value in parentheses. * for p < .1, ** for p < .05, and *** for p < .01*

Sources: House values are from single-family mortgages either purchased or securitized by Fannie Mae or Freddie Mac. Weather information is obtained from the National Oceanic and Atmospheric Administration. Household demographics and industry characteristics are from the United States Census Bureau

In the third robustness check, consideration is given to how the industry types affect the estimates (exhibit 10). Sensitivity is tested by creating subsample selections for the top 10 MSAs in each type of industry. The magnitude of the estimate is sometimes different across different types of industry, but the patterns for the weather controls provide support for common trends with the previous findings. The results are likely confounded by overlaps across sample selections.

Exhibit 10

Seasonality Effects Based on Industry Concentration

Estimate	H.C.S.A.	MFG	PS	Retail	Education	F.I.R.E.	Public Admin	Constrn.	Transp.	Agriculture
Weather										
Range Temp Q1	0.032*** (15.92)	0.020*** (9.52)	0.017*** (4.56)	0.018*** (7.41)	0.022*** (9.55)	0.027*** (13.90)	0.014*** (6.59)	0.004* (1.83)	0.014*** (8.18)	0.009*** (4.33)
Range Temp Q2	0.008*** (3.91)	0.009*** (4.23)	0.016*** (4.24)	– 0.000 (– 0.14)	0.002 (0.80)	0.009*** (4.84)	0.007*** (3.18)	– 0.001 (– 0.44)	0.004** (2.37)	0.000 (0.03)
Range Temp Q3	0.020*** (9.94)	0.008*** (3.90)	0.000 (0.00)	0.004* (1.68)	0.011*** (4.74)	0.013*** (6.52)	0.005** (2.30)	– 0.008*** (– 3.55)	0.003 (1.60)	0.001 (0.70)
Range Temp	– 0.014*** (– 3.63)	– 0.011*** (– 2.80)	– 0.002 (– 0.21)	– 0.007 (– 1.42)	– 0.007 (– 1.51)	– 0.006 (– 1.63)	– 0.004 (– 0.97)	– 0.001 (– 0.18)	– 0.007* (– 1.81)	– 0.000 (– 0.07)
Average	0.001 (0.75)	0.001 (0.79)	– 0.000 (– 0.04)	0.003 (1.34)	0.001 (0.32)	0.001 (0.64)	– 0.005** (– 2.51)	– 0.001 (– 0.37)	– 0.001 (– 0.49)	0.000 (0.14)
Precipitation	0.022 (1.02)	0.012 (0.58)	– 0.039 (– 1.40)	– 0.004 (– 0.44)	0.007 (0.29)	– 0.018 (– 1.12)	– 0.011 (– 0.62)	0.006 (1.23)	– 0.004 (– 0.47)	– 0.002 (– 0.17)
Characteristics										
ln (Number of Sales)	– 0.105 (– 1.29)	– 0.185*** (– 3.02)	– 0.130 (– 1.24)	– 0.108* (– 1.78)	0.015 (0.18)	– 0.165*** (– 2.67)	– 0.151** (– 2.10)	– 0.003 (– 0.05)	– 0.282*** (– 4.69)	– 0.125** (– 1.98)
Over 65 Years Old	– 3.775** (– 2.48)	0.034 (0.64)	0.290*** (2.59)	– 0.695* (– 1.66)	0.383*** (4.56)	– 0.263* (– 1.71)	– 0.122** (– 2.23)	0.178*** (4.15)	0.047 (1.12)	– 0.021 (– 0.39)
Pct of Nonwhite	0.354** (2.24)	0.043*** (3.46)	0.035*** (3.20)	– 0.424* (– 1.69)	– 0.002 (– 0.19)	0.025*** (3.11)	0.011** (2.09)	0.003 (0.04)	– 0.005 (– 0.68)	– 0.005 (– 0.56)
Pct of Bachelor or Higher	0.225** (2.35)	– 0.063*** (– 2.65)	– 0.024 (– 0.21)	– 0.687 (– 1.63)	– 0.149*** (– 4.39)	0.065*** (4.28)	0.019 (0.79)	0.155 (1.12)	0.033*** (4.31)	0.046*** (2.91)
Pct of Single-Family Sales	– 1.141** (– 2.54)	– 0.068*** (– 7.36)	0.001 (0.01)	– 0.310* (– 1.66)	– 0.011 (– 0.87)	0.003 (0.40)	– 0.001 (– 0.05)	0.030 (0.15)	– 0.077* (– 1.84)	0.055*** (2.89)
Year Spline										
Year [1991,1998]	0.014 (0.94)	0.030** (1.98)	0.072*** (3.00)	– 0.012 (– 0.96)	0.038** (2.32)	0.030** (2.29)	0.003 (0.21)	0.009 (0.60)	0.024** (2.04)	0.026* (1.95)
Year [1999,2007]	0.147*** (12.63)	0.107*** (8.62)	0.155*** (8.21)	0.111*** (10.67)	0.114*** (8.53)	0.131*** (12.17)	0.173*** (14.51)	0.091*** (7.51)	0.094*** (9.61)	0.093*** (8.54)
Year [2008,2011]	0.023 (0.82)	0.146*** (5.19)	0.072* (1.68)	– 0.039 (– 1.58)	0.104*** (3.20)	0.079*** (3.08)	0.020 (0.71)	0.128*** (4.55)	0.015 (0.64)	0.001 (0.03)
Year [2012,2020]	– 0.040** (– 2.37)	0.027 (1.62)	0.093*** (3.67)	0.035** (2.40)	– 0.010 (– 0.51)	– 0.029* (– 1.90)	– 0.019 (– 1.15)	0.009 (0.54)	– 0.006 (– 0.46)	0.011 (0.71)
Goodness of Fit										
R^2	0.509	0.538	0.405	0.305	0.444	0.511	0.459	0.435	0.431	0.361
BIC	3,025	3,207	4,242	2,805	3,440	2,907	3,148	3,071	2,546	2,879
N	1,195	1,196	1,198	1,189	1,199	1,196	1,197	1,187	1,195	1,196

Industry categories are abbreviated as HCSA = Healthcare and Social Assistance, MFG = Manufacturing, PS = Professional Services, FIRE = Finance, Insurance, and Real Estate, Constrn. = Construction, and Transp. = Transportation.
*Notes: The difference between NSA HPI and SA HPI is models as a function of weather-related variables, social and industry characteristics, and temporal and geographic controls. Quarterly frequency. Range Temp is defined as the difference between the maximum and minimum temperature. Columns are ordered based on how popular the industries are, and the 10 most popular industries are listed. Top 100 MSA are included in the models. N is calculated by the number of State/MSA×120. t-value in parentheses. * for $p < .1$, ** for $p < .05$, and *** for $p < .01$.*
Sources: House values are from single-family mortgages either purchased or securitized by Fannie Mae or Freddie Mac. Weather information is obtained from the National Oceanic and Atmospheric Administration. Household demographics and industry characteristics are from the United States Census Bureau

For the last robustness check, the sensitivity of previous findings are tested by using two alternative household samples. In exhibit 11, the regression results from model 5 are separated by the distribution of the percentage of white and older than 65 years old. The MSAs are grouped by 10th, 25th, 75th, and 90th quantiles of the respective demographic control. The patterns for the results in each subsample are coincident with the main findings. Meanwhile, the findings further suggest that in cities with more diversity (i.e., a lower percentage of white), the weather controls have higher influence on seasonality in house prices. MSAs with a higher percentage of aging people are more likely to be impacted by weather-related variables.

Exhibit 11

The Lack of Population Diversity and Seasonality

	White				Over 65 Years Old			
Estimate	**10%**	**25%**	**75%**	**90%**	**10%**	**25%**	**75%**	**90%**
Weather								
Range Temp Q1	0.007* (1.72)	0.018*** (10.27)	0.021*** (14.86)	0.024*** (11.17)	0.008*** (3.62)	0.009*** (5.82)	0.032*** (23.12)	0.037*** (16.03)
Range Temp Q2	0.011*** (3.00)	0.008*** (4.72)	0.008*** (5.34)	0.005*** (2.61)	0.007*** (3.12)	0.006*** (3.61)	0.011*** (7.61)	0.009*** (3.92)
Range Temp Q3	0.005 (– 1.39)	0.006*** (3.69)	0.007*** (5.28)	0.009*** (4.48)	0.008*** (– 3.46)	0.006*** (– 4.18)	0.020*** (14.64)	0.023*** (10.11)
Range Temp	– 0.002 (– 0.30)	– 0.008** (– 2.42)	– 0.001 (– 0.24)	– 0.000 (– 0.02)	– 0.001 (– 0.16)	– 0.001 (– 0.27)	– 0.014*** (– 5.22)	– 0.015*** (– 3.44)
Average	– 0.004 (– 1.14)	– 0.002 (– 1.24)	0.003** (2.38)	0.002 (0.90)	– 0.002 (– 0.83)	0.000 (0.29)	0.002* (1.73)	0.004* (1.83)
Precipitation	– 0.043* (– 1.76)	– 0.024** (– 1.99)	– 0.002 (– 0.17)	– 0.004 (– 0.19)	0.005 (0.85)	0.002 (0.38)	0.002 (0.22)	0.004 (0.33)
Year Spline								
Year [1991-1998]	0.011 (0.49)	0.021* (1.92)	0.015 (1.40)	0.014 (0.88)	0.024 (1.57)	0.017 (1.63)	0.006 (0.64)	– 0.004 (– 0.26)
Year [1999-2007]	0.172*** (9.94)	0.132*** (15.07)	0.146*** (16.61)	0.125*** (10.20)	0.136*** (10.94)	0.127*** (14.68)	0.141*** (19.56)	0.150*** (13.67)
Year [2008-2011]	– 0.007 (– 0.18)	0.045** (2.21)	0.069*** (3.41)	0.128*** (4.32)	0.130*** (4.51)	0.110*** (5.43)	– 0.016 (– 0.94)	– 0.029 (– 1.12)
Year [2012-2020]	0.098*** (4.22)	0.022* (1.84)	0.023* (1.85)	0.013 (0.76)	0.002 (0.09)	0.042*** (3.49)	– 0.007 (– 0.66)	0.009 (0.59)
Controls								
Household Char	Y	Y	Y	Y	Y	Y	Y	Y
Industry Shares	Y	Y	Y	Y	Y	Y	Y	Y
Fixed Effect	MSA	MSA	MSA	MSA	MSA	MSA	MSA	MSA
Goodness of Fit								
R^2	0.396	0.401	0.472	0.487	0.492	0.468	0.466	0.472
BIC	4,570	9,684	8,417	3,188	3,706	9,083	7,039	3,328
N	1,317	3,232	2,983	1,199	1,318	3,115	2,864	1,309
Num. MSA	11	27	25	10	11	26	24	11
Percentile	≤10%	≤25%	≥75%	≥90%	≤10%	≤25%	≥75%	≥90%

*Notes: The difference between NSA HPI and SA HPI is models as a function of weather-related variables, social and industry characteristics, and temporal and geographic controls. Quarterly frequency. Range Temp is defined as the difference between the maximum and minimum temperature. Hawaii is not included because of missing data on weather. N is calculated by number of MSA×120. t-value in parentheses. * for p < .1, ** for p < .05, and *** for p < .01.*

Sources: House values are from single-family mortgages either purchased or securitized by Fannie Mae or Freddie Mac. Weather information is obtained from the National Oceanic and Atmospheric Administration. Household demographics and industry characteristics are from the United States Census Bureau

Conclusions

Using the FHFA HPI data, this study explores seasonality in house prices at both State and MSA levels. The FHFA HPI has long used the Census Bureau's X-12 procedure to adjust for seasonality. This report shows that X-13, a successor to X-12, can be used to recalculate the entire suite of public indices provided by FHFA and offer adjustments that have not been provided for 400 metropolitan areas and other geographies. The new adjusted indices yield some improvements but indicate that the resulting optimization does not change drastically over time in real estate markets. Frequent recalculations yield limited upside and may even invite model specification risks. For example, with the COVID-19 pandemic, adjustment routines and forecasts perform poorly when including the recent period. For pre-COVID periods, the growing seasonal impact is tested against impacts from changes in weather, social and industry concentrations, temporal trends, and geographic controls. Fluctuations are muted in locations with thicker housing markets, weather controls give minor improvements, and time trends are the strongest driver, which suggests it is crucial to provide adjusted indices, but regular updates are less necessary.

Appendix

The Repeat-Sales Methodology

This report uses housing price index data, repeat-sales from FHFA. The repeat-sales methodology is explained in the following section. The explicit intertemporal hedonic model measures house prices by involving a dummy variable for each index period.

$$P_{it} = x_{it}^{'}\beta + D_{t}^{'}\delta + \epsilon_{it}, \tag{4}$$

where $\boldsymbol{x}$ is a vector of property characteristics; $\boldsymbol{\beta}$ denotes the vector of estimated coefficients for the attributes; $\boldsymbol{\delta}$ is a vector of estimated coefficients for each of the time dummies; and D_t, the time dummies, are set equal to 1 if the i^{th} house is sold in period t, otherwise 0. Taking the difference between the second sale price and the first sale price, the following is obtained

$$P_{it}^{2} - P_{it}^{1} = (x_{2,it}^{'}\beta - x_{1,it}^{'}\beta) + (D_{2,t}^{'}\delta - D_{1,t}^{'}\delta) + (\epsilon_{2,it} - \epsilon_{1,it}). \tag{5}$$

Under the assumption that the vectors of physical and location characteristics do not change over time, the equation (2) can be simplified to

$$P_{it}^{2} - P_{it}^{1} = (D_{2,t}^{'}\delta - D_{1,t}^{'}\delta) + (\epsilon_{2,it} - \epsilon_{1,it}), \tag{6}$$

which is usually corrected further under the assumption that the change in the estimated transaction prices is a function of the time between sales.

Simulation

As alluded to earlier, a series of simulations were used before evaluating actual house price data and applying an optimal seasonality adjustment. A white noise process was seeded over a substantial period. After that, several typical problems are introduced by simple models: moving average, autoregression, and time trend processes. For a simple time series model, autocorrelations and partial autocorrelations can help identify the order of an MA or AR model. The diagnosis gets complicated when combining the moving average, the autoregressive, and the time trend process into one series. Proper data generation adjustments are extremely hard to determine when multiple events happen at once.

White Noise Process

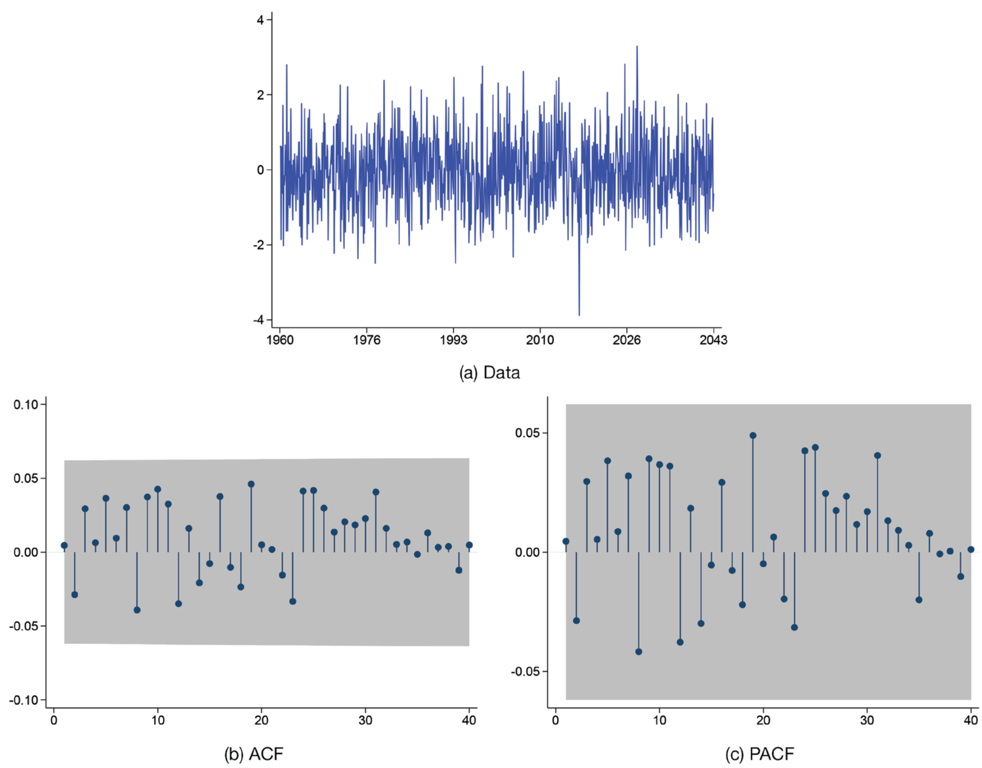
A sequence y_t is white noise process, and y_t is a sequence of independent and identically distributed standard normal random variables:

$$y_t \sim iidN\,(0{,}1). \tag{7}$$

Exhibit A-1 shows the autocorrelation and partial autocorrelation plots and finds that all the autocorrelations and the partial autocorrelations are close to 0. In practice, if all the partial autocorrelations are not statistically significantly different from 0, then the series is a white noise series.

Exhibit A-1

White Noise Process



Source: Data generation is simulated by the authors to replicate the desired process

Moving Average Process

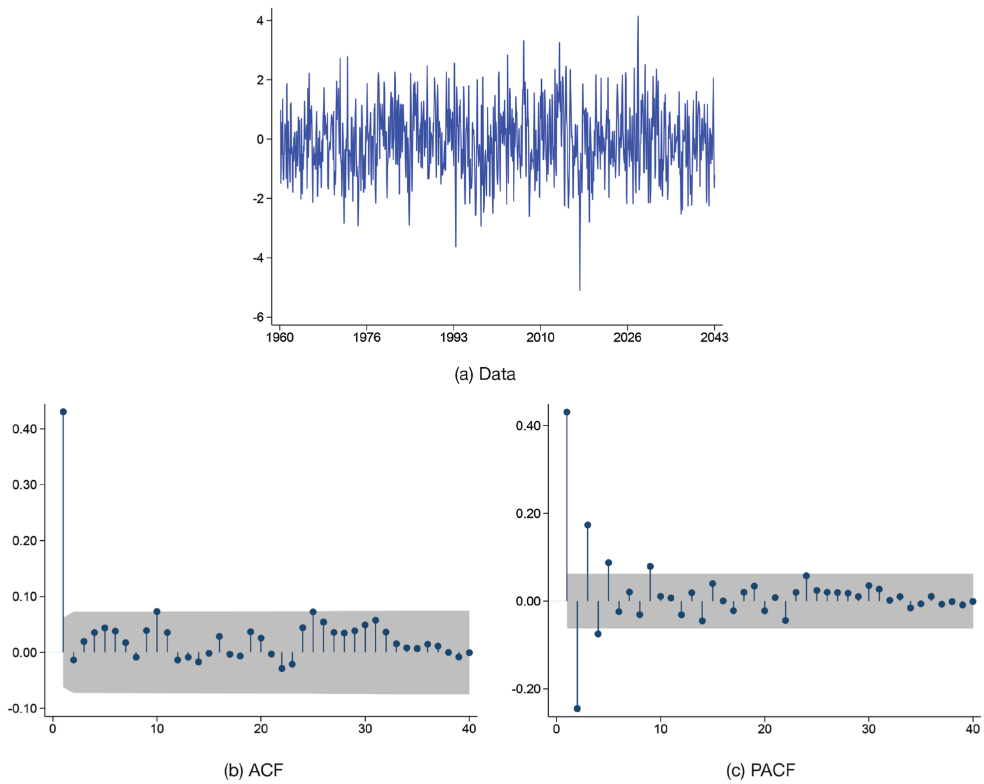
The moving average process is a function of the current and lagged unobserved shocks, a sequence of iid random variables with mean zero. Exhibit A-2 shows the plot of the first-order moving average process, and the formula can be written as

$$y_t = \epsilon_t + 0.6\epsilon_{t-1}, \tag{8}$$

where $\epsilon_t \sim iidN(0,1)$.

Exhibit A-2

First-Order Moving Average Process



Source: Data generation is simulated by the authors to replicate the desired process

In the example, the first lag of the shock positively affects the current value of the series. Exhibit A-2 shows the autocorrelation and partial autocorrelation plots and finds that the only term that is statistically significant from 0 in the autocorrelation plot is lag 1. The partial autocorrelation plot shows declining significant terms that are alternating in sign. Empirically, the autocorrelation function is helpful in identifying the order of an MA model.

Autoregressive Process

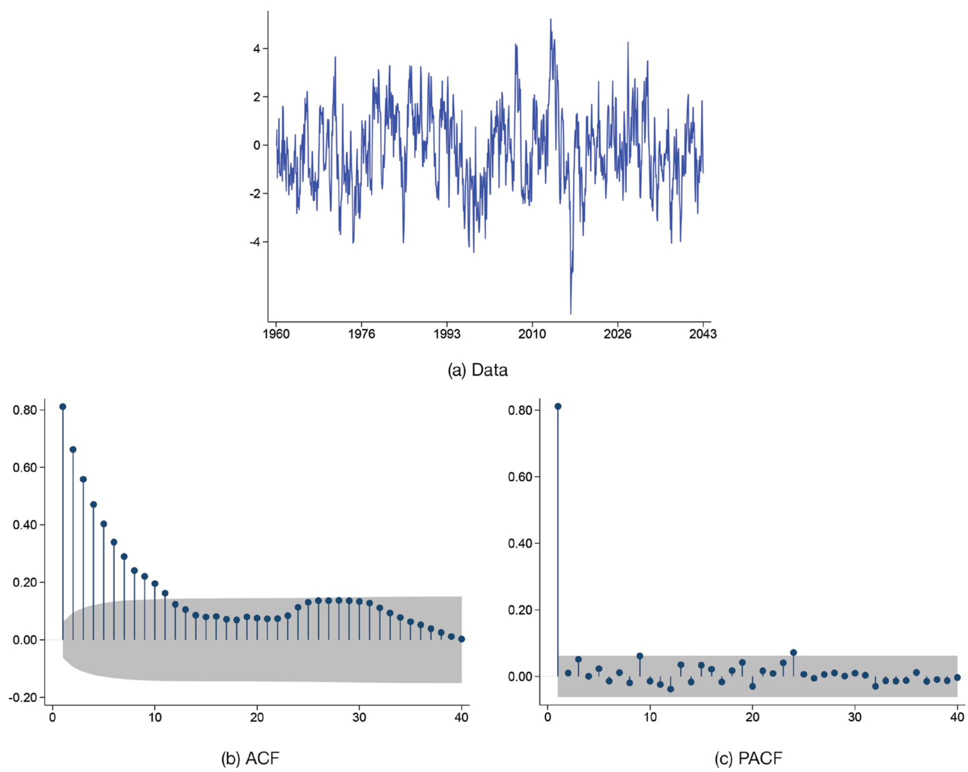
The autoregressive process shows that a series' current value is linearly related to its past values, plus an additive stochastic shock, a sequence of iid random variables with a mean zero. Exhibit A-3 shows the plot of the first-order autoregressive process, and the formula can be written as

$$y_t = 0.8y_{t-1} + \epsilon_t, \tag{9}$$

where $\epsilon_t \sim iidN(0, 1)$. This model is like the well-known simple regression model, in which y_t is the dependent variable and y_{t-1} is the explanatory variables. Usually, the absolute value of the coefficient on y_{t-1} is less than 1 to create a convergent geometric series.

Exhibit A-3

First-Order Autoregressive Process



Source: Data generation is simulated by the authors to replicate the desired process

In the example, the last period's value positively affects the current value. Exhibit A-3 shows the autocorrelation and partial autocorrelation plots: the autocorrelation plot shows declining significant terms at a slow rate, and for the partial autocorrelations, there is one large and statistically significant term. In practice, the partial autocorrelation function is a useful tool for determining the order p of an AR model.

Time Trend Process

The time trend process shows that the current value is a function of time. Exhibit A-4 shows the plot of the time trend process, and the formula can be written as

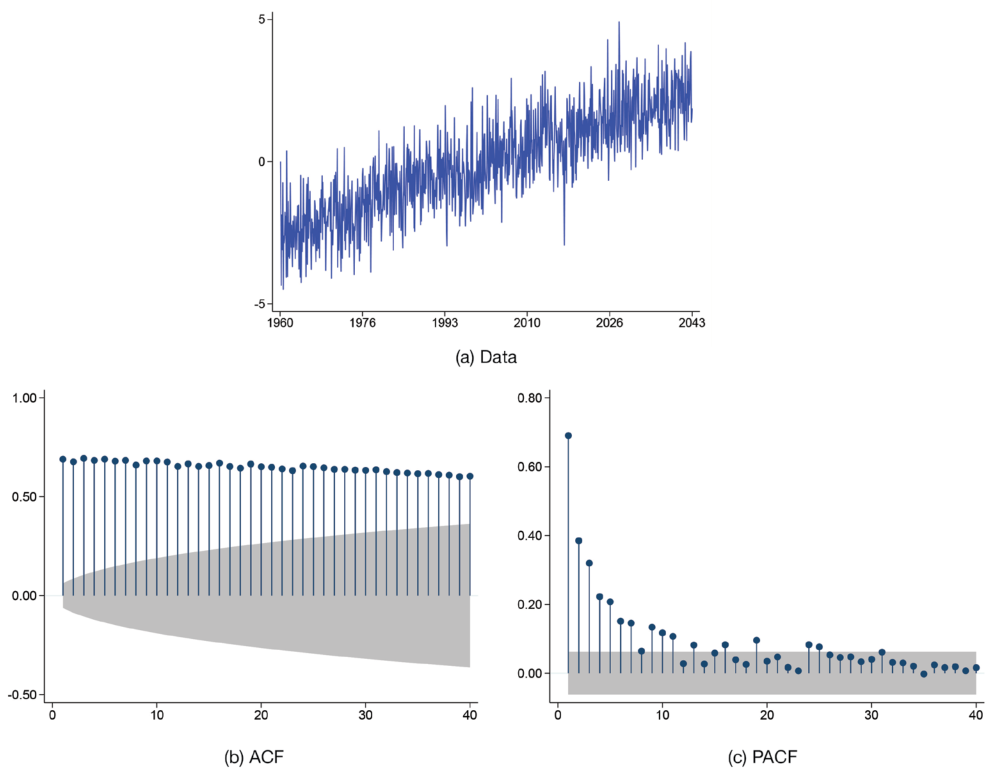
$$y_t = -2.5 + 0.005t = \epsilon_t, \tag{10}$$

where $\epsilon_t \sim iidN(0, 1)$.

In the example here, the value has increased by 0.5 percent each year. Exhibit A-4 shows the autocorrelation and partial autocorrelation plots: the autocorrelation plot shows declining significant terms at a slow rate, and for the partial autocorrelations, there are declining significant terms at a fast rate.

Exhibit A-4

Time Trend Process



Source: Data generation is simulated by the authors to replicate the desired process

Mixed Model Process

The final example combines the moving average, the autoregressive, and the time trend process into one series. Exhibit A-5 shows the plot of the mixed model, and the formula becomes

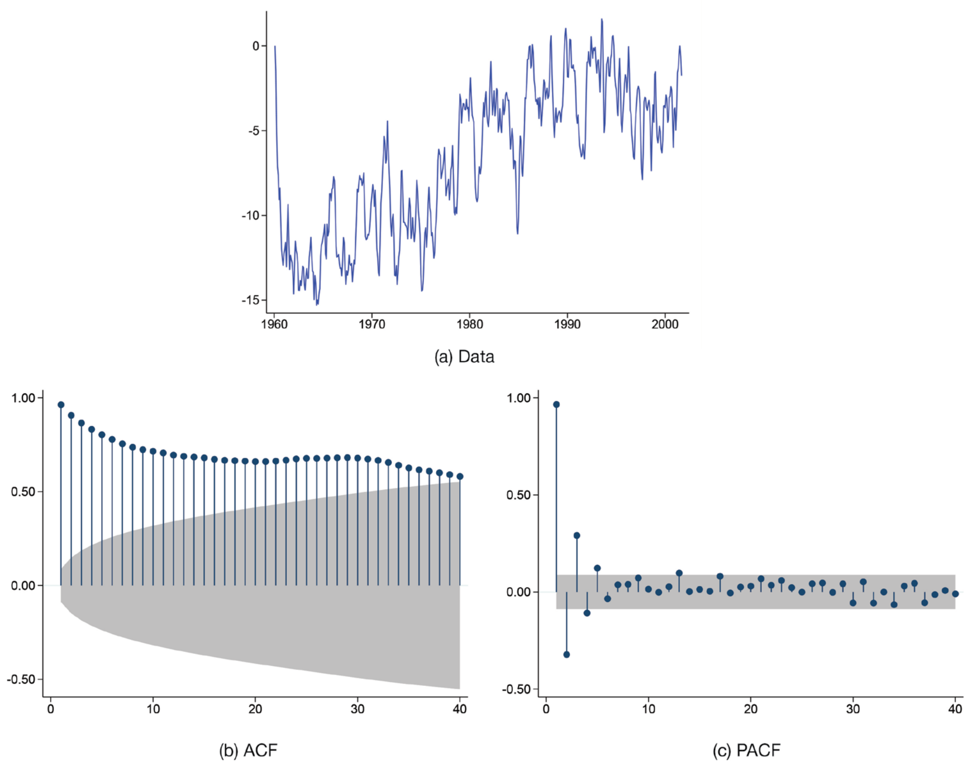
$$y_t = -2.5 + 0.6\epsilon_{t-1} + 0.8y_{t-1} + 0.005t + \epsilon_t, \tag{11}$$

where $\epsilon_t \sim iidN(0,1)$.

Exhibit A-5 shows the autocorrelation and partial autocorrelation plots. Based on the autocorrelation and partial autocorrelation, it is extremely difficult to determine suitable adjustments when multiple events are happening simultaneously. This statement is true even for simple simulation models, and it becomes even more applicable in real-world data examples.

Exhibit A-5

Mixed Model Process



Source: Data generation is simulated by the authors to replicate the desired process

X-13ARIMA-SEATS are used to find the optimal ARIMA model. Exhibit A-6 shows the regression results. The automated routine doesn't yield the exact ARIMA structure because of the mixed nature with (p, d, q) terms that mix AR and MA effects. The MA(1) specification is an infinite-order of AR model. Exhibit A-7 shows the autocorrelation and partial autocorrelation after being adjusted, and it suggests that the fit is very good, given that none of the terms for AC and PAC are statistically significant. Although one "optimal" term structure will be chosen by the software, data users should realize that, in practice, several term structures could be close and equally plausible.

Exhibit A-6

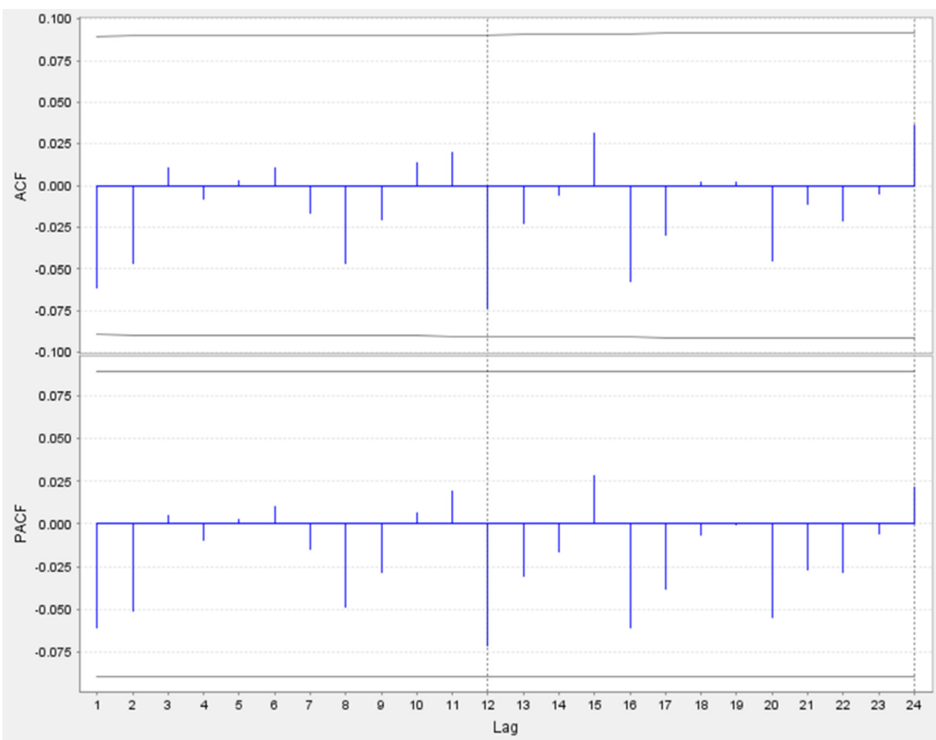
Regression Results for ARIMA Model

Parameter	Estimate
Nonseasonal AR	
Lag 1	0.784*** (0.042)
Nonseasonal MA	
Lag 1	0.344*** (0.046)
Lag 2	0.584*** (0.037)
Test	P-value
Ljung-Box	1.00
ARIMA Model	(1, 1, 2)

Source: Data generation is simulated by the authors to replicate the desired process

Exhibit A-7

AC and PAC after Adjusted by X-13ARIMA-SEATS



Source: Data generation is simulated by the authors to replicate the desired process

Approximate Production Time

Exhibit A-8

Approximate Production Time

Index Type and Geography	Time	SA Available?	New SA Computed?
Purchase-Only Indices (Estimated using Sales Price Data)			
United States and Census Divisions	15 min	Y	Y
States	1.5 hr	Y	Y
100 Largest Metropolitan Statistical Areas	2.5 hrs	Y	Y
Select Metropolitan Areas—Distress-Free Measures	30 min	Y	Y
Puerto Rico	3 min	Y	Y
Manufactured Homes	3 min	N	Y
All-Transactions Indices (Estimated using Sales Prices and Appraisal Data)			
United States and Census Divisions	15 min	N	Y
States	90 min	N	Y
Metropolitan Statistical Areas and Divisions	24 hrs	N	Y
State Nonmetropolitan Areas	1.5 hrs	N	Y
Puerto Rico	3 min	N	Y
Three-Digit ZIP Codes		N	N
Manufactured Homes	3 min	N	Y
Expanded-Data Indices (Estimated using Enterprise, FHA, and County Recorder Price Data)			
United States (1975Q1–Present)	3 min	N	Y
United States and Census Divisions	15 min	Y	Y
States	1.5 hrs	Y	Y
50 Largest Metropolitan Statistical Areas	1.6 hrs	Y	Y

Source: Calculations performed by the authors

Exhibit A-9

The Impact of Seasonality on House Price Measures (1 of 2)

Estimate	State					MSA				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 1	Model 2	Model 3	Model 4	Model 5
Weather										
Range Temp Q1	0.014*** (11.58)	0.017*** (13.46)	0.015*** (15.59)	0.016*** (11.00)	0.011*** (9.93)	0.018*** (18.69)	0.017*** (18.60)	0.018*** (23.29)	0.016*** (17.45)	0.018*** (23.80)
Range Temp Q2	0.010*** (10.28)	0.006*** (4.66)	0.008*** (7.84)	0.005*** (3.27)	0.014*** (10.25)	0.005*** (5.45)	0.006*** (6.56)	0.005*** (6.92)	0.008*** (9.28)	0.006*** (7.45)
Range Temp Q3	0.020*** (12.92)	0.011*** (5.13)	0.016*** (9.38)	0.009*** (2.91)	0.027*** (11.14)	0.006*** (5.87)	0.006*** (6.97)	0.006*** (7.44)	0.008*** (9.38)	0.006*** (7.92)
Range Temp	– 0.018*** (– 7.78)	– 0.014*** (– 5.95)	– 0.016*** (– 8.36)	– 0.013*** (– 5.29)	– 0.018*** (– 9.04)	– 0.003** (– 2.01)	– 0.001 (– 0.57)	– 0.004*** (– 3.15)	– 0.004** (– 2.41)	– 0.005*** (– 3.41)
Average Temp	– 0.017*** (– 11.73)	– 0.003 (– 1.30)	– 0.011*** (– 6.26)	0.003 (0.93)	– 0.025*** (– 8.78)	– 0.003*** (– 3.33)	0.002** (2.47)	0.001 (1.02)	0.003*** (3.77)	0.001* (1.94)
Precipitation	– 0.032*** (– 3.36)	– 0.014 (– 1.31)	– 0.018** (– 2.14)	– 0.006 (– 0.54)	– 0.013 (– 1.48)	– 0.010** (– 2.25)	– 0.014*** (– 3.02)	– 0.021*** (– 5.38)	– 0.000 (– 0.07)	– 0.004 (– 0.95)
Characteristics										
ln (Number of Sales)		– 0.192*** (– 9.27)	0.044** (2.43)	– 0.609*** (– 19.05)	0.004 (0.11)		– 0.182*** (– 12.86)	– 0.035*** (– 2.93)	– 0.605*** (– 23.43)	– 0.084*** (– 3.57)
Over 65 Years Old		– 0.066*** (– 4.83)	– 0.028** (– 2.53)	7.962*** (13.34)	3.162*** (6.24)		– 0.022*** (– 3.14)	0.001 (0.19)	0.358*** (2.77)	0.307*** (2.86)
Pct of Nonwhite		– 0.000 (– 0.21)	– 0.006*** (– 3.93)	1.329*** (13.48)	0.513*** (6.13)		– 0.007*** (– 4.71)	– 0.006*** (– 4.64)	0.124*** (6.62)	0.058*** (3.73)
Pct of Bachelor or Higher		0.027*** (4.26)	0.022*** (4.32)	4.341*** (13.54)	1.664*** (6.11)		0.071*** (14.21)	0.077*** (18.70)	– 0.202*** (– 5.17)	– 0.006 (– 0.18)
Pct of Single-Family Sales		0.015*** (5.04)	0.008*** (3.35)	1.664*** (13.35)	0.666*** (6.30)		– 0.010*** (– 4.78)	0.000 (0.19)	0.077*** (4.39)	0.061*** (4.19)
Industry Concentration Shares										
H.C.A.S.		0.040*** (2.91)	– 0.026** (– 2.37)	15.581*** (13.24)	5.852*** (5.86)		0.047*** (4.58)	0.031*** (3.62)	– 0.065 (– 0.92)	0.063 (1.08)
Manufacturing		0.032*** (4.55)	0.011* (1.88)	18.701*** (13.39)	7.143*** (6.02)		0.039*** (7.24)	0.030*** (6.72)	0.446*** (7.86)	0.274*** (5.80)
Professional Services		0.126*** (8.48)	0.050*** (4.06)	20.445*** (13.50)	7.835*** (6.08)		0.015 (1.39)	– 0.009 (– 0.94)	1.647*** (7.54)	0.774*** (4.25)
Retail		– 0.015 (– 0.89)	– 0.006 (– 0.45)	41.494*** (13.38)	16.171*** (6.15)		0.078*** (5.22)	0.078*** (6.29)	0.288** (2.49)	0.216** (2.24)
Education		– 0.090*** (– 6.08)	– 0.017 (-1.40)	25.238*** (13.31)	9.808*** (6.10)		– 0.092*** (– 7.60)	– 0.069*** (– 6.90)	1.918*** (6.26)	0.937*** (3.67)
F.I.R.E.		– 0.013 (-1.15)	– 0.005 (– 0.52)	16.771*** (13.31)	6.430*** (6.01)		0.004 (0.47)	– 0.016** (– 2.30)	– 0.280** (– 2.45)	– 0.150 (-1.58)
Public Administrations		– 0.034*** (– 3.69)	0.019** (2.49)	18.228*** (13.26)	7.033*** (6.04)		0.019*** (2.89)	0.021*** (3.73)	– 0.521*** (– 3.59)	– 0.155 (-1.28)
Construction		– 0.083*** (– 4.12)	– 0.090*** (– 5.60)	7.499*** (12.47)	2.677*** (5.26)		– 0.002 (– 0.11)	0.001 (0.04)	1.137*** (3.93)	0.796*** (3.31)
Transportation		0.050** (2.47)	– 0.009 (– 0.54)	29.988*** (13.50)	11.483*** (6.08)		0.091*** (7.08)	0.065*** (6.14)	0.699*** (7.02)	0.595*** (7.18)
Agriculture		0.072*** (7.00)	0.047*** (5.70)	17.144*** (13.42)	6.559*** (6.04)		0.046*** (5.31)	0.044*** (6.21)	-1.277*** (– 3.07)	– 0.706** (– 2.05)

Exhibit A-9

The Impact of Seasonality on House Price Measures (2 of 2)

Estimate	State					MSA				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 1	Model 2	Model 3	Model 4	Model 5
Year Spline										
Year [1991,1998]			0.023*** (3.85)		0.027*** (4.48)			0.020*** (3.76)		0.021*** (4.08)
Year [1999,2007]			0.100*** (21.20)		0.099*** (21.06)			0.127*** (29.78)		0.126*** (30.54)
Year [2008,2011]			0.107*** (9.69)		0.103*** (9.03)			0.075*** (7.69)		0.071*** (7.34)
Year [2012,2020]			– 0.009 (– 1.37)		– 0.006 (– 0.88)			0.014** (2.34)		0.015*** (2.68)
Fixed Effect				State	State				MSA	MSA
Goodness of Fit										
R^2	0.099	0.171	0.467	0.231	0.494	0.034	0.111	0.389	0.185	0.438
BIC	16,835	16,465	13,847	16,322	13,842	38,684	37,832	33,373	37,579	33,177
N	6,000	6,000	6,000	6,000	6,000	11,963	11,963	11,963	11,963	11,963

*Notes: The difference between NSA HPI and SA HPI is models as a function of weather-related variables, social and industry characteristics, and temporal and geographic controls. Quarterly frequency. Range Temp is defined as the difference between the maximum and minimum temperature. Hawaii is not included because of missing data on weather. Industries are ordered based on popularity, and the 10 most popular industries are listed. Top 100 MSA are included in the models. N is calculated by the number of States/MSA*120. t-value in parentheses. * for p < .1, ** for p < .05, and *** for p < .01.*

Sources: House values are from single-family mortgages either purchased or securitized by Fannie Mae or Freddie Mac. Weather information is obtained from the National Oceanic and Atmospheric Administration. Household demographics and industry characteristics are from the United States Census Bureau

Exhibit A-10

Splitting up Seasonality by Quantile (1 of 2)

Estimate	State					MSA				
	0.1	0.25	0.5	0.75	0.9	0.1	0.25	0.5	0.75	0.9
Weather										
Range Temp Q1	0.005*** (3.89)	0.011*** (11.74)	0.015*** (14.05)	0.018*** (13.40)	0.019*** (10.39)	0.006*** (8.98)	0.012*** (15.78)	0.017*** (21.92)	0.022*** (19.95)	0.024*** (15.75)
Range Temp Q2	0.004*** (3.33)	0.006*** (6.29)	0.007*** (6.06)	0.006*** (4.61)	0.004** (2.18)	0.002*** (3.03)	0.003*** (4.72)	0.003*** (3.96)	0.002* (1.65)	0.001 (0.75)
Range Temp Q3	0.007*** (3.52)	0.011*** (7.13)	0.015*** (8.11)	0.018*** (7.99)	0.015*** (4.78)	0.003*** (5.17)	0.006*** (7.66)	0.006*** (8.04)	0.006*** (5.49)	0.007*** (4.37)
Range Temp	– 0.005** (– 2.18)	– 0.009*** (– 5.03)	– 0.010*** (– 4.85)	– 0.010*** (– 3.98)	– 0.014*** (– 4.06)	– 0.001 (– 0.52)	– 0.004*** (– 3.19)	– 0.004*** (– 3.04)	– 0.003* (– 1.81)	– 0.005** (– 2.18)
Average	– 0.005** (– 2.23)	– 0.007*** (– 3.82)	– 0.011*** (– 5.24)	– 0.014*** (– 5.74)	– 0.012*** (– 3.48)	– 0.000 (– 0.10)	– 0.001 (– 0.97)	– 0.001 (– 0.91)	0.001 (0.85)	0.002 (1.46)
Precipitation	– 0.004 (– 0.43)	– 0.005 (– 0.60)	– 0.006 (– 0.61)	– 0.007 (– 0.63)	– 0.008 (– 0.50)	– 0.001 (– 0.33)	– 0.005 (– 1.35)	– 0.008** (– 2.03)	– 0.020*** (– 3.73)	– 0.038*** (– 5.06)
Characteristics										
In (Number of Sales)	0.046** (2.15)	0.078*** (4.51)	0.053*** (2.67)	0.013 (0.52)	– 0.059* (– 1.76)	0.018* (1.77)	0.036*** (3.11)	0.007 (0.61)	– 0.052*** (– 3.06)	– 0.136*** (– 5.83)
Over 65 Years Old	0.003 (0.26)	– 0.012 (-1.11)	– 0.029** (– 2.34)	– 0.016 (-1.07)	– 0.054*** (– 2.59)	0.010** (2.07)	0.011** (1.98)	0.012** (2.00)	0.008 (1.02)	– 0.010 (– 0.88)
Pct of Nonwhite	0.000 (0.02)	– 0.004*** (– 2.69)	– 0.005*** (– 3.10)	– 0.003 (-1.53)	– 0.003 (-1.06)	– 0.002** (– 2.37)	– 0.004*** (– 3.43)	– 0.003** (– 2.03)	– 0.004** (– 2.05)	– 0.006** (– 2.53)

Exhibit A-10

Splitting up Seasonality by Quantile (2 of 2)

Estimate	State					MSA				
	0.1	0.25	0.5	0.75	0.9	0.1	0.25	0.5	0.75	0.9
Characteristics										
Pct of Bachelor or Higher	0.009 (1.40)	0.014*** (2.89)	0.012** (2.14)	0.012 (1.64)	0.033*** (3.42)	0.014*** (4.04)	0.017*** (4.19)	0.036*** (8.61)	0.059*** (10.00)	0.082*** (10.22)
Pct of Single-Family Sales	0.010*** (3.42)	0.007*** (2.89)	0.002 (0.94)	0.007** (2.03)	0.003 (0.65)	0.002 (1.42)	0.004** (2.57)	0.002 (1.18)	0.000 (0.01)	– 0.010*** (– 2.79)
Industry Concentration Shares										
H.C.S.A.	– 0.010 (– 0.75)	– 0.035*** (– 3.27)	– 0.023* (-1.90)	– 0.006 (– 0.40)	0.023 (1.10)	– 0.006 (– 0.81)	– 0.001 (– 0.18)	0.017* (1.96)	0.034*** (2.83)	0.045*** (2.77)
Manufacturing	0.006 (0.95)	0.007 (1.20)	0.007 (1.01)	0.011 (1.32)	0.014 (1.30)	0.007** (1.99)	0.015*** (3.56)	0.024*** (5.23)	0.017*** (2.58)	0.026*** (2.95)
Professional Services	0.012 (0.82)	– 0.006 (– 0.47)	0.012 (0.90)	0.064*** (3.83)	0.093*** (4.03)	– 0.007 (– 0.97)	0.003 (0.37)	0.005 (0.52)	– 0.004 (– 0.34)	– 0.012 (– 0.66)
Retail	– 0.017 (-1.04)	– 0.024* (-1.76)	– 0.015 (– 0.96)	0.002 (0.09)	0.046* (1.76)	– 0.011 (-1.08)	– 0.010 (– 0.81)	0.033*** (2.64)	0.022 (1.23)	0.043* (1.80)
Education	– 0.011 (– 0.78)	– 0.001 (– 0.10)	0.011 (0.85)	0.006 (0.36)	– 0.046** (– 2.03)	– 0.013 (-1.52)	– 0.010 (-1.08)	– 0.025** (– 2.49)	– 0.052*** (– 3.68)	–0.108*** (– 5.57)
F.I.R.E.	0.003 (0.24)	0.002 (0.24)	0.020** (2.02)	0.006 (0.47)	– 0.027 (-1.62)	0.002 (0.36)	0.011 (1.57)	– 0.001 (– 0.17)	– 0.027*** (– 2.73)	–0.055*** (– 3.99)
Public Admin	0.010 (1.17)	0.016** (2.29)	0.017** (2.11)	0.021** (2.03)	0.023* (1.65)	0.007 (1.58)	0.014*** (2.59)	0.018*** (3.19)	0.010 (1.30)	0.012 (1.08)
Construction	– 0.025 (-1.30)	– 0.049*** (– 3.15)	– 0.060*** (– 3.38)	– 0.064*** (– 2.90)	– 0.106*** (– 3.51)	– 0.006 (– 0.60)	– 0.008 (– 0.71)	– 0.014 (-1.19)	– 0.004 (– 0.22)	– 0.001 (– 0.03)
Transportation	0.004 (0.23)	0.001 (0.07)	– 0.007 (– 0.37)	– 0.018 (– 0.81)	– 0.042 (-1.36)	0.007 (0.83)	0.010 (0.98)	0.031*** (2.92)	0.038** (2.53)	0.056*** (2.70)
Agriculture	0.011 (1.15)	0.010 (1.19)	0.032*** (3.45)	0.059*** (5.13)	0.100*** (6.36)	0.007 (1.15)	0.002 (0.36)	0.029*** (4.00)	0.045*** (4.46)	0.060*** (4.37)
Year Spline										
Year [1991-1998]	0.015** (2.10)	0.018*** (3.11)	0.020*** (3.08)	0.019** (2.33)	0.026** (2.39)	0.009** (2.03)	0.015*** (2.93)	0.018*** (3.49)	0.016** (2.11)	0.018* (1.75)
Year [1999-2007]	0.028*** (5.03)	0.064*** (14.19)	0.091*** (17.43)	0.119*** (18.24)	0.132*** (14.89)	0.028*** (8.01)	0.069*** (17.03)	0.117*** (27.27)	0.165*** (27.28)	0.207*** (25.09)
Year [2008-2011]	0.049*** (3.75)	0.076*** (7.22)	0.119*** (9.79)	0.144*** (9.46)	0.183*** (8.85)	0.041*** (5.04)	0.072*** (7.73)	0.087*** (8.83)	0.103*** (7.40)	0.098*** (5.16)
Year [2012-2020]	0.016** (– 2.08)	– 0.019*** (– 3.08)	– 0.019*** (– 2.65)	– 0.011 (– 1.26)	0.005 (0.37)	– 0.020*** (– 4.14)	– 0.031*** (– 5.61)	– 0.014** (– 2.42)	0.008 (0.92)	0.061** (5.47)
Goodness of Fit										
R^2	0.092	0.199	0.312	0.387	0.438	0.064	0.149	0.260	0.332	0.373
N	6,000	6,000	6,000	6,000	6,000	11,963	11,963	11,963	11,963	11,963

*Notes: The difference between NSA HPI and SA HPI is models as a function of weather-related variables, social and industry characteristics, and temporal and geographic controls. Quarterly frequency. Range Temp is defined as the difference between the maximum and minimum temperature. Hawaii is not included because of missing data on weather. Industries are ordered based on popularity, and the 10 most popular industries are listed. Top 100 MSA are included in our models. N is calculated by the number of States/MSA*120. T-value in parentheses. * for p < .1, ** for p < .05, and *** for p < .01.*

Sources: House values are from single-family mortgages either purchased or securitized by Fannie Mae or Freddie Mac. Weather information is obtained from the National Oceanic and Atmospheric Administration. Household demographics and industry characteristics are from the United States Census Bureau

Exhibit A-11

Stratifying Seasonality by Time-between-Sales (1 of 2)

Estimate	State			MSA		
	Short Time	Average Time	Long Time	Short Time	Average Time	Long Time
Weather						
Range Temp Q1	0.010*** (5.13)	0.011*** (6.44)	0.014*** (5.89)	0.011*** (10.19)	0.022*** (19.43)	0.022*** (13.56)
Range Temp Q2	0.010*** (4.30)	0.012*** (5.58)	0.018*** (7.58)	0.002 (1.48)	0.007*** (5.94)	0.009*** (5.58)
Range Temp Q3	0.025*** (5.83)	0.019*** (4.95)	0.038*** (8.11)	– 0.001 (– 0.95)	0.011*** (9.63)	0.009*** (5.62)
Range Temp	– 0.017*** (– 5.46)	– 0.013*** (– 3.76)	– 0.023*** (– 6.31)	0.001 (0.56)	– 0.009*** (– 4.01)	– 0.009*** (– 2.86)
Average	– 0.023*** (– 4.35)	– 0.021*** (– 4.38)	– 0.035*** (– 6.47)	0.003** (2.42)	0.001 (0.86)	– 0.000 (– 0.01)
Precipitation	– 0.027* (– 1.67)	– 0.025 (– 1.40)	0.010 (0.73)	– 0.004 (– 0.54)	0.005 (0.59)	– 0.007 (– 1.11)
Characteristics						
In (Number of Sales)	0.016 (0.30)	0.148** (2.32)	0.063 (1.04)	0.036 (0.76)	– 0.111*** (– 2.71)	– 0.147*** (– 3.14)
Over 65 Years Old	0.055 (1.24)	– 0.094* (-1.79)	– 0.060 (– 0.97)	0.178*** (3.16)	0.032 (0.92)	– 0.272 (-1.49)
Pct of Nonwhite	– 0.020* (-1.86)	0.003 (0.21)	0.050*** (2.87)	– 0.014** (– 2.00)	– 0.039*** (– 2.80)	– 0.021 (– 0.72)
Pct of Bachelor or Higher	– 0.081** (– 2.20)	0.353** (2.04)	0.063** (2.08)	0.182*** (6.21)	– 0.041 (– 0.86)	0.263 (1.46)
Pct of Single-Family Sales	– 0.058*** (– 2.63)	0.045*** (4.23)	– 0.021 (-1.08)	0.016 (1.32)	0.107*** (3.47)	0.033 (1.32)
Industry Concentration Shares						
H.C.S.A.	– 0.399** (– 2.49)	– 0.227*** (– 5.90)	– 0.364** (– 2.02)	– 0.135* (-1.76)	– 0.087 (-1.59)	0.381** (2.57)
Manufacturing	– 0.192** (– 2.23)	– 0.168* (-1.72)	0.126* (1.88)	0.110** (2.16)	0.143*** (3.04)	– 0.423 (-1.08)
Professional Services	– 0.158* (-1.85)	– 0.741* (-1.78)	– 0.577** (– 2.46)	– 0.277*** (– 3.34)	0.314*** (5.48)	– 0.380 (– 0.71)
Retail	– 0.046 (– 0.75)	0.777*** (4.83)	0.506** (2.47)	0.181 (1.50)	0.827*** (5.84)	– 0.055 (– 0.33)
Education	0.032 (0.49)	0.401** (2.14)	0.371** (2.46)	– 0.184*** (– 3.19)	0.675*** (3.56)	0.304 (1.47)
F.I.R.E.	0.029 (0.39)	– 0.546 (-1.48)	– 0.390*** (– 2.74)	– 0.015 (– 0.21)	0.138*** (5.28)	-1.195 (-1.19)
Public Admin	– 0.099 (-1.09)	– 0.392 (-1.57)	0.310*** (3.39)	0.061 (1.10)	0.182*** (4.52)	– 0.286 (-1.21)
Construction	– 0.253*** (– 3.21)	– 0.314** (-1.99)	0.598** (2.14)	0.492*** (4.76)	– 0.386*** (– 3.44)	-1.414 (-1.07)
Transportation	– 0.087 (-1.02)	– 0.313*** (– 3.35)	0.707*** (3.41)	0.165*** (2.78)	0.317*** (3.12)	0.192 (0.79)
Agriculture	– 0.218** (– 2.16)	– 0.118 (– 0.90)	– 0.758*** (– 2.60)	– 0.269 (-1.30)	0.201*** (2.68)	0.563 (1.55)

Exhibit A-11

Stratifying Seasonality by Time-between-Sales (2 of 2)

	State			MSA		
Estimate	**Short Time**	**Average Time**	**Long Time**	**Short Time**	**Average Time**	**Long Time**
Year Spline						
Year [1991,1998]	0.030*** (2.85)	0.013 (1.26)	0.023** (2.27)	0.005 (0.55)	0.021*** (2.60)	0.026** (2.54)
Year [1999,2007]	0.074*** (9.48)	0.115*** (13.66)	0.118*** (14.17)	0.121*** (17.13)	0.134*** (20.53)	0.128*** (15.79)
Year [2008,2011]	0.102*** (5.19)	0.127*** (6.41)	0.110*** (5.50)	0.132*** (7.85)	0.029* (1.86)	0.065*** (3.55)
Year [2012,2020]	– 0.007 (– 0.67)	– 0.000 (– 0.04)	– 0.024** (– 2.06)	– 0.007 (– 0.67)	– 0.001 (– 0.15)	0.045*** (4.17)
Fixed Effect	MSA	MSA	MSA	MSA	MSA	
Goodness of Fit						
R^2	0.420	0.556	0.521	0.462	0.480	0.406
BIC	4,693	4,334	4,780	10,446	9,973	12,361
N	2,040	1,920	2,040	3,940	3,953	4,070
Num. State/MSA	17	16	17	33	33	34
Percentile	<33%	34%-66%	>67%	<33%	34%-66%	>67%

*Notes: The difference between NSA HPI and SA HPI is models as a function of weather-related variables, social and industry characteristics, and temporal and geographic controls. Quarterly frequency. Range Temp is defined as the difference between the maximum and minimum temperature. Hawaii is not included because of missing data of weather. Shortest Time cities are defined if the time between sales is in the lower 10 percent among the top 100 MSA; Less Time cities are between 10 and 25 percent; Average cities are between 25 and 75 percent; More Time cities are between 75 and 90 percent; Longest Time cities are higher than 90 percent. N is calculated by the number of States/MSA*120. t-value in parentheses. * for p < .1, ** for p < .05, and *** for p < .01.*

Sources: House values are from single-family mortgages either purchased or securitized by Fannie Mae or Freddie Mac. Weather information is obtained from the National Oceanic and Atmospheric Administration. Household demographics and industry characteristics are from the United States Census Bureau

Exhibit A-12

The Impact of Seasonality by City Size (1 of 2)

Estimate	**Smallest City**	**Small City**	**Medium City**	**Large City**	**Largest City**
Weather					
Range Temp Q1	0.011*** (4.80)	0.016*** (11.07)	0.017*** (15.01)	0.020*** (10.96)	0.033*** (14.73)
Range Temp Q2	0.002 (0.75)	0.002 (1.16)	0.007*** (6.02)	0.009*** (4.79)	0.007*** (3.22)
Range Temp Q3	0.006*** (2.66)	0.007*** (4.81)	0.004*** (3.10)	0.006*** (3.18)	0.022*** (10.12)
Range Temp	0.005 (1.01)	– 0.007** (– 2.36)	– 0.005** (– 2.20)	– 0.006 (– 1.55)	– 0.014*** (– 3.52)
Average	0.003 (1.57)	– 0.000 (– 0.01)	0.002** (2.19)	0.000 (0.11)	– 0.003 (– 1.64)
Precipitation	0.027* (1.94)	0.011 (0.89)	– 0.018** (– 2.23)	– 0.000 (– 0.10)	– 0.006 (– 0.33)
Characteristics					
In (Number of Sales)	– 0.373*** (– 4.33)	– 0.099* (-1.92)	– 0.059 (-1.56)	– 0.023 (– 0.41)	0.019 (0.21)
Over 65 Years Old	0.350* (1.68)	0.047 (1.63)	– 0.150 (-1.36)	– 0.292 (– 0.40)	– 0.094 (-1.59)

Exhibit A-12

The Impact of Seasonality by City Size (2 of 2)

Estimate	Smallest City	Small City	Medium City	Large City	Largest City
Characteristics					
Pct of Nonwhite	0.047 (1.11)	– 0.040*** (– 6.82)	0.005 (0.30)	– 0.031 (– 0.47)	– 0.033*** (– 2.81)
Pct of Bachelor or Higher	0.008 (0.35)	– 0.191*** (– 5.29)	0.456** (2.38)	0.017 (0.19)	0.000 (.)
Pct of Single-Family Sales	0.116** (1.96)	0.019** (2.14)	– 0.053 (-1.49)	0.027 (0.74)	0.000 (.)
Industry Concentration Shares					
H.C.S.A.	– 0.529** (– 2.25)	0.092* (1.88)	0.733*** (3.22)	0.354 (0.48)	0.000 (.)
Manufacturing	– 0.115*** (– 4.72)	0.099*** (3.71)	– 0.186 (– 0.61)	– 0.229 (– 0.46)	0.000 (.)
Professional Services	0.098 (1.01)	0.136*** (3.04)	-1.497* (-1.66)	0.000 (.)	0.000 (.)
Retail	– 0.759** (– 2.55)	– 0.320*** (– 3.37)	– 0.891 (-1.21)	0.000 (.)	0.000 (.)
Education	0.293 (1.22)	0.300*** (7.02)	– 2.049** (– 2.10)	0.000 (.)	0.000 (.)
F.I.R.E.	0.000 (.)	0.450*** (5.42)	0.058 (0.26)	0.000 (.)	0.000 (.)
Public Admin	0.000 (.)	0.134*** (3.76)	– 0.443 (-1.19)	0.000 (.)	0.000 (.)
Construction	0.000 (.)	0.227*** (4.90)	1.271*** (4.01)	0.000 (.)	0.000 (.)
Transportation	0.000 (.)	– 0.299*** (– 6.22)	– 2.140 (-1.55)	0.000 (.)	0.000 (.)
Agriculture	0.000 (.)	0.034* (1.69)	0.367 (0.70)	0.000 (.)	0.000 (.)
Year Spline					
Year [1991,1998]	0.026 (1.54)	0.025** (2.41)	0.019** (2.46)	0.027** (2.31)	0.037*** (2.61)
Year [1999,2007]	0.104*** (7.84)	0.090*** (10.66)	0.142*** (22.02)	0.121*** (13.00)	0.104*** (8.57)
Year [2008,2011]	0.024 (0.77)	0.031 (1.54)	0.076*** (5.07)	0.103*** (4.91)	0.078*** (3.06)
Year [2012,2020]	0.053*** (2.83)	0.004 (0.35)	0.038*** (4.31)	– 0.039*** (– 3.14)	– 0.030** (– 2.02)
Fixed Effect	MSA	MSA	MSA	MSA	MSA
Goodness of Fit					
R^2	0.411	0.398	0.452	0.471	0.481
BIC	3,269	4,045	18,116	4,495	2,588
N	1,186	1,794	6,109	1,798	1,076
Num. MSA	10	15	51	15	9
Percentile	<10%	10%-25%	25-75%	75%-90%	>90%

*Notes: The difference between NSA HPI and SA HPI is models as a function of weather-related variables, social and industry characteristics, and temporal and geographic controls. Quarterly frequency. Range Temp is defined as the difference between the maximum and minimum temperature. Hawaii is not included because of missing data on weather. Tiny cities are defined if the populations are in the lower 10 percent of the top 100 MSA; Small cities are in the lower 25 percent; Median cities are between 25 and 75 percent; large cities are higher than 75 percent; Huge cities are higher than 90 percent. N is calculated by the number of States/MSA*120. t-value in parentheses. * for p < .1, ** for p < .05, and *** for p < .01.*

Sources: House values are from single-family mortgages either purchased or securitized by Fannie Mae or Freddie Mac. Weather information is obtained from the National Oceanic and Atmospheric Administration. Household demographics and industry characteristics are from the United States Census Bureau

Exhibit A-13

Stratifying Seasonality by Calendar Quarter

Estimate	State				MSA			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Weather								
Range Temp	– 0.020*** (– 4.31)	0.002 (0.41)	0.006 (1.36)	– 0.004 (-1.30)	0.001 (0.20)	0.008*** (3.73)	– 0.002 (– 0.87)	0.003 (1.29)
Average	– 0.015*** (– 3.53)	0.003 (0.74)	– 0.016*** (– 3.88)	0.003 (0.72)	0.000 (0.17)	0.001 (0.77)	– 0.001 (-1.10)	0.000 (0.32)
Precipitation	– 0.019 (– 0.83)	– 0.002 (– 0.12)	– 0.014 (– 0.91)	– 0.001 (– 0.09)	– 0.016 (-1.48)	– 0.044*** (– 5.22)	– 0.031*** (– 4.04)	– 0.011** (-2.02)
Characteristics								
In (Number of Sales)	0.006 (0.14)	0.131*** (4.56)	0.044 (1.49)	0.009 (0.26)	– 0.015 (– 0.58)	– 0.018 (– 0.80)	0.009 (0.45)	– 0.103*** (– 4.36)
Over 65 Years Old	0.007 (0.26)	– 0.120*** (– 6.77)	0.036** (1.98)	– 0.065*** (– 3.20)	0.017 (1.37)	0.011 (1.05)	0.031*** (3.22)	– 0.050*** (– 4.38)
Pct of Nonwhite	– 0.002 (– 0.41)	– 0.012*** (– 4.44)	– 0.009*** (– 3.53)	– 0.008** (-2.58)	– 0.012*** (– 4.46)	– 0.002 (– 0.74)	– 0.007*** (– 3.22)	– 0.002 (– 0.77)
Pct of Bachelor or Higher	0.021 (1.63)	0.045*** (5.44)	0.013 (1.56)	0.027*** (2.91)	0.043*** (4.79)	0.112*** (14.94)	0.055*** (8.06)	0.098*** (12.03)
Pct of Single-Family Sales	0.002 (0.30)	0.028*** (7.33)	– 0.009** (-2.40)	0.014*** (3.21)	– 0.003 (– 0.71)	0.012*** (3.89)	– 0.005* (-1.73)	– 0.001 (– 0.28)
Industry Concentration Shares								
H.C.A.S.	– 0.031 (-1.09)	0.040** (2.30)	– 0.073*** (– 4.01)	– 0.026 (-1.31)	0.027 (1.44)	0.036** (2.32)	0.013 (0.95)	0.046*** (2.73)
Manufacturing	0.028* (1.93)	0.002 (0.20)	0.005 (0.52)	– 0.006 (– 0.53)	0.027*** (2.74)	0.044*** (5.33)	0.013* (1.70)	0.034*** (3.84)
Professional Services	0.061** (1.97)	0.038* (1.96)	0.016 (0.77)	0.056** (2.50)	0.002 (0.10)	0.012 (0.70)	– 0.048*** (– 3.21)	– 0.001 (– 0.08)
Retail	– 0.023 (– 0.66)	0.020 (0.88)	– 0.058** (-2.51)	0.052** (2.08)	– 0.016 (– 0.59)	0.123*** (5.45)	– 0.009 (– 0.46)	0.207*** (8.47)
Education	– 0.006 (– 0.21)	– 0.079*** (– 4.09)	0.031 (1.55)	– 0.048** (-2.18)	0.025 (1.13)	–0.124*** (– 6.82)	0.006 (0.37)	– 0.174*** (– 8.80)
F.I.R.E.	– 0.014 (– 0.63)	– 0.006 (– 0.43)	0.003 (0.17)	– 0.011 (– 0.70)	0.021 (1.38)	– 0.022* (-1.73)	– 0.017 (-1.43)	– 0.047*** (– 3.39)
Public Admin	0.018 (1.00)	0.041*** (3.54)	0.008 (0.62)	0.010 (0.73)	0.021* (1.77)	0.022** (2.21)	0.015* (1.69)	0.019* (1.74)
Construction	– 0.114*** (-2.87)	– 0.028 (-1.10)	– 0.183*** (– 6.86)	– 0.068** (-2.36)	– 0.044* (-1.74)	0.080*** (3.81)	– 0.086*** (– 4.51)	0.066*** (2.94)
Transportation	0.012 (0.29)	– 0.039 (-1.48)	0.027 (1.00)	– 0.054* (-1.84)	0.055** (2.35)	0.082*** (4.25)	0.044** (2.48)	0.079*** (3.73)
Agriculture	0.060*** (3.00)	0.020 (1.54)	0.061*** (4.28)	0.059*** (4.01)	0.024 (1.53)	0.064*** (4.91)	0.042*** (3.54)	0.043*** (3.03)
Year Spline								
Year [1991,1998]	0.023 (1.56)	0.006 (0.59)	0.035*** (3.62)	0.016 (1.51)	0.013 (1.15)	0.018* (1.88)	0.022** (2.57)	0.026** (2.46)
Year [1999,2007]	0.142*** (12.21)	0.096*** (13.00)	0.106*** (13.72)	0.059*** (6.94)	0.168*** (18.05)	0.120*** (15.46)	0.139*** (19.76)	0.081*** (9.61)
Year [2008,2011]	0.158*** (5.73)	0.107*** (6.16)	0.123*** (6.89)	0.044** (2.23)	0.115*** (5.35)	0.121*** (6.78)	0.021 (1.32)	0.042** (2.19)
Year [2012,2020]	– 0.083*** (– 5.19)	0.036*** (3.54)	– 0.067*** (– 6.32)	0.072*** (6.19)	– 0.079*** (– 6.31)	0.065*** (6.19)	– 0.026*** (-2.73)	0.097*** (8.47)
Goodness of Fit								
R^2	0.448	0.588	0.552	0.382	0.379	0.529	0.403	0.370
BIC	4,181	2,835	2,941	3,215	8,976	7,891	7,306	8,377
N	1,500	1,500	1,500	1,500	2,991	2,992	2,993	2,987

*Notes: The difference between NSA HPI and SA HPI is models as a function of weather-related variables, social and industry characteristics, and temporal and geographic controls. Quarterly frequency. Range Temp is defined as the difference between the maximum and minimum temperature. Hawaii is not included because of missing data on weather. Industries are ordered based on popularity, and the 10 most popular industries are listed. Top 100 MSA are included in the models. N is calculated by the number of States/MSA*120. t-value in parentheses. * for p < .1, ** for p < .05, and *** for p < .01.*

Sources: House values are from single-family mortgages either purchased or securitized by Fannie Mae or Freddie Mac. Weather information is obtained from the National Oceanic and Atmospheric Administration. Household demographics and industry characteristics are from the United States Census Bureau

Exhibit A-14

The Lack of Population Diversity and Seasonality (1 of 2)

Estimate	White				Over 65 Years Old			
	10%	25%	75%	90%	10%	25%	75%	90%
Weather								
Range Temp Q1	0.007*	0.018***	0.021***	0.024***	0.008***	0.009***	0.032***	0.037***
	(1.72)	(10.27)	(14.86)	(11.17)	(3.62)	(5.82)	(23.12)	(16.03)
Range Temp Q2	0.011***	0.008***	0.008***	0.005***	0.007***	0.006***	0.011***	0.009***
	(3.00)	(4.72)	(5.34)	(2.61)	(3.12)	(3.61)	(7.61)	(3.92)
Range Temp Q3	– 0.005	0.006***	0.007***	0.009***	– 0.008***	– 0.006***	0.020***	0.023***
	(– 1.39)	(3.69)	(5.28)	(4.48)	(– 3.46)	(– 4.18)	(14.64)	(10.11)
Range Temp	– 0.002	– 0.008**	– 0.001	– 0.000	– 0.001	– 0.001	– 0.014***	– 0.015***
	(– 0.30)	(– 2.42)	(– 0.24)	(– 0.02)	(– 0.16)	(– 0.27)	(– 5.22)	(– 3.44)
Average	– 0.004	– 0.002	0.003**	0.002	– 0.002	0.000	0.002*	0.004*
	(– 1.14)	(– 1.24)	(2.38)	(0.90)	(– 0.83)	(0.29)	(1.73)	(1.83)
Precipitation	– 0.043*	– 0.024**	– 0.002	– 0.004	0.005	0.002	0.002	0.004
	(– 1.76)	(– 1.99)	(– 0.17)	(– 0.19)	(0.85)	(0.38)	(0.22)	(0.33)
Characteristics								
ln (Number of Sales)	– 0.255***	– 0.150***	– 0.079	0.070	0.081	0.022	– 0.189***	– 0.178***
	(– 2.79)	(– 3.18)	(-1.33)	(0.82)	(1.13)	(0.44)	(– 4.22)	(– 2.83)
Over 65 Years Old	0.340**	0.389***	– 0.140***	– 0.165	– 0.954***	– 0.472**	– 0.469***	– 0.911
	(2.19)	(4.32)	(– 2.91)	(-1.16)	(– 3.69)	(– 2.26)	(– 3.78)	(-1.11)
Pct of Nonwhite	– 0.076***	– 0.044**	0.017	– 0.095	– 0.039***	– 0.035**	0.076***	0.200
	(– 2.60)	(– 2.48)	(0.45)	(– 0.96)	(– 7.18)	(– 2.52)	(3.61)	(1.32)
Pct of Bachelor or Higher	0.057***	0.025	0.284***	– 0.219***	0.007	0.038	0.687***	0.470
	(2.77)	(0.29)	(2.70)	(– 4.80)	(0.20)	(1.24)	(3.96)	(1.42)
Pct of Single-Family Sales	0.034**	0.030	0.012	– 0.042	0.051***	– 0.140***	0.112***	0.106**
	(2.28)	(0.99)	(0.42)	(-1.25)	(3.29)	(– 3.35)	(3.23)	(2.24)
Industry Concentration Shares								
H.C.A.S.	– 0.046	– 0.190***	0.146*	0.363**	– 0.302*	– 0.224**	0.696***	0.241
	(– 0.37)	(– 3.20)	(1.81)	(2.21)	(-1.96)	(– 2.01)	(5.42)	(0.63)
Manufacturing	0.002	– 0.108	0.019	– 0.114***	– 0.156***	– 0.165**	– 0.333**	0.146
	(0.19)	(– 0.99)	(0.24)	(– 4.72)	(– 7.13)	(– 2.53)	(– 2.25)	(0.72)
Professional Services	0.000	0.095	– 0.022	0.063	0.170	– 0.351	– 0.689***	– 2.390
	(.)	(0.76)	(– 0.29)	(0.21)	(1.63)	(-1.59)	(– 3.02)	(-1.25)
Retail	0.000	0.072	0.808***	– 0.371	0.000	– 0.098	2.671***	4.133
	(.)	(0.42)	(4.00)	(– 0.68)	(.)	(-1.10)	(4.42)	(1.09)
Education	0.000	0.062	0.031	– 0.593***	0.000	– 0.278***	0.199***	0.000
	(.)	(0.18)	(0.22)	(– 5.98)	(.)	(– 4.23)	(4.45)	(.)
F.I.R.E.	0.000	– 0.172**	– 0.415**	0.000	0.000	– 0.407***	0.409***	0.000
	(.)	(– 2.17)	(– 2.06)	(.)	(.)	(– 2.96)	(6.20)	(.)
Public Administration	0.000	– 0.123	– 0.153	0.000	0.000	– 0.192***	– 0.177	0.000
	(.)	(– 0.80)	(-1.05)	(.)	(.)	(– 2.78)	(-1.20)	(.)
Construction	0.000	– 0.168	0.497	0.000	0.000	– 0.690***	– 0.889***	0.000
	(.)	(– 0.83)	(1.36)	(.)	(.)	(– 4.22)	(– 3.75)	(.)
Transportation	0.000	– 0.015	0.709***	0.000	0.000	– 0.097	0.128	0.000
	(.)	(– 0.07)	(3.33)	(.)	(.)	(– 0.77)	(0.85)	(.)
Agriculture	0.000	– 0.082	-1.129	0.000	0.000	– 0.083	0.797***	0.000
	(.)	(– 0.33)	(-1.15)	(.)	(.)	(-1.10)	(3.73)	(.)

Exhibit A-14

The Lack of Population Diversity and Seasonality (2 of 2)

Estimate	White				Over 65 Years Old			
	10%	25%	75%	90%	10%	25%	75%	90%
Year Spline								
Year [1991-1998]	0.011 (0.49)	0.021* (1.92)	0.015 (1.40)	0.014 (0.88)	0.024 (1.57)	0.017 (1.63)	0.006 (0.64)	– 0.004 (– 0.26)
Year [1999-2007]	0.172*** (9.94)	0.132*** (15.07)	0.146*** (16.61)	0.125*** (10.20)	0.136*** (10.94)	0.127*** (14.68)	0.141*** (19.56)	0.150*** (13.67)
Year [2008-2011]	– 0.007 (– 0.18)	0.045** (2.21)	0.069*** (3.41)	0.128*** (4.32)	0.130*** (4.51)	0.110*** (5.43)	– 0.016 (– 0.94)	– 0.029 (– 1.12)
Year [2012-2020]	0.098*** (4.22)	0.022* (1.84)	0.023* (1.85)	0.013 (0.76)	0.002 (0.09)	0.042*** (3.49)	– 0.007 (– 0.66)	0.009 (0.59)
Fixed Effect	MSA	MSA	MSA	MSA	MSA	MSA	MSA	MSA
Goodness of Fit								
R^2	0.396	0.401	0.472	0.487	0.492	0.468	0.466	0.472
BIC	4,570	9,684	8,417	3,188	3,706	9,083	7,039	3,328
N	1,317	3,232	2,983	1,199	1,318	3,115	2,864	1,309
Num. MSA	11	27	25	10	11	26	24	11
Percentile	≤10%	≤25%	≥75%	≥90%	≤10%	≤25%	≥75%	≥90%

*Notes: The difference between NSA HPI and SA HPI is models as a function of weather-related variables, social and industry characteristics, and temporal and geographic controls. Quarterly frequency. Range Temp is defined as the difference between the maximum and minimum temperature. Hawaii is not included because of missing data on weather. N is calculated by the number of MSA*120. t-value in parentheses. * for p < .1, ** for p < .05, and *** for p < .01.*

Sources: House values are from single-family mortgages either purchased or securitized by Fannie Mae or Freddie Mac. Weather information is obtained from the National Oceanic and Atmospheric Administration. Household demographics and industry characteristics are from the United States Census Bureau

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Housing Supply and Liquidity in the COVID-19 Era

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The analysis and conclusions are those of the authors alone and should not be represented or interpreted as conveying an official position, policy, analysis, opinion, or endorsement of either the Federal Housing Finance Agency or the U.S. government. Any errors or omissions are the sole responsibility of the authors.

Abstract

This report documents changes in national housing supply and liquidity during the COVID-19 era using a suite of monthly indices, ranging from summary statistics (mean and median time on the market, proportion of homes sold, etc.) to more advanced econometric indices that can address censoring and unobserved heterogeneity. The results indicate a sharp structural break in most of the indices near the start of COVID-19 in March 2020, though each index's most likely break date varies by a few months. The findings suggest that the start of the pandemic saw a supply decrease, followed by an immediate and sustained price increase. Listings became more likely to be withdrawn, but those that sold did so faster relative to pre-COVID-19 levels, indicating a change in the distribution of housing market liquidity. Finally, the results suggest that there were different types of structural breaks, specifically changes in the level, slope, and seasonality of the indices.

Introduction

COVID-19 caused major disruptions to the health and the economy of the United States.[1] One large sector of the economy that COVID-19 has impacted is the housing market. For example, the Federal Housing Finance Agency House Price Index (FHFA HPI®) reveals unprecedented price appreciation during the COVID period, with year-over-year (seasonally adjusted) appreciation sustaining double-digit increases since October 2020. Additionally, the media has pointed out

[1] For example, as Mutikani (2021) points out, the Bureau of Economic Analysis reported a decrease of annualized GDP of 19.2 percent from the fourth quarter of 2019 to the second quarter of 2020. Additionally, Kennedy (2022) argues there may be longer term consequences to the U.S. economy.

that COVID-19 has affected home construction (Mutikani, 2020), interest rates and refinancing (Goodman and Klein, 2022), and migration (Taylor, 2020), among other things. While much attention has been paid by the press and academic literature on COVID-19's effects on home prices, less attention has been paid to COVID's effects on housing market supply[2] and liquidity.[3] As far as the authors are aware, there is no systematic study of the effects of COVID-19 on housing supply and liquidity.[4] This report aims to fill this gap.

To fill this gap, a suite of housing market supply and liquidity indicators are constructed at the national level. Several indices are used, in part because there is no single, agreed-upon index, but also because by considering them jointly affords a more holistic view of the housing market. The indicators are housing market indices that range in sophistication from basic summary statistics to more advanced econometric measures (Carrillo and Williams, 2019). The results suggest three stylized facts. First, there is evidence of structural breaks at the start of COVID-19 in March 2020 for all but one of the market indicators, though the most likely break for an index occurred a few months before or after March 2020, depending upon the index. Second, the advanced econometric indices, which are constructed to address unobserved heterogeneity and censoring, appear to break later than the simpler indices, which do not control for these factors. Thus, the results provide evidence for the importance of addressing these two fundamental issues when measuring housing market supply and liquidity. Finally, there is evidence of different types of structural changes that vary from index to index. These structural breaks include changes in the level, changes in slope, and also changes in the seasonality of each index.

Unobserved heterogeneity across properties, and changes in the composition of homes during the pandemic are subjects of concern. For example, it may be the case that homes that transacted prior to COVID have different characteristics compared to those that transacted after the start of the pandemic.[5] Additionally, COVID-19 may have changed market conditions directly of its own accord. Hence, an analysis of housing market liquidity would be incomplete without considering how the number of homes available for sale, particularly those that didn't sell, changed during the COVID-era. To remedy this, some indices are investigated that use information from all listings, including those that did not sell.

[2] Note that this report does not consider new construction, so that the analysis of supply is restricted to the supply of pre-existing homes.

[3] D'Lima, Lopez, and Pradhan (2022) find a 1.5 percent price decrease in densely populated areas and a 1.4 percent price increase in relatively sparsely populated areas in response to shutdown orders. Wang (2021) and Zhang, Leonard, and Bitzan (2022) both find evidence of price increases in several different areas of the United States. Zhao (2022) finds evidence of price increases early in the pandemic. Finally, Duca, Hoesli, and Montezuma (2021) and Yiu (2021) consider international housing market responses and argue that interest rates were important in driving home prices.

[4] This work is most closely related to Yoruk (2022), who finds decreases in home sales and the number of new listings since the start of the pandemic in March 2020.

[5] For example, D'Lima, Lopez, and Pradhan (2022) show different price trends in rural versus urban areas, suggesting demand and preference changes. If homes are systematically different in rural versus urban areas, which seems plausible, then changing composition will be a factor in estimating either price appreciation or liquidity.

The indices on supply and liquidity used in this report complement the more typical indices for homes prices.[6] For example, after learning that prices have increased, knowing whether or not liquidity or supply was constrained can lead to different policy conclusions. Additionally, several papers in the literature have documented that there may exist a lead-lag relationship between price and time on the market during the Great Recession, so that changes in the latter can be used to predict changes in the former.[7] This report finds similar results. Specifically, there is evidence of a negative relationship between price and time on the market (TOM) in the COVID era, with price increases and TOM generally decreasing as the pandemic progressed.[8] This report builds off of several recent papers in the literature that have constructed new methods of estimating housing market liquidity, most notably Carrillo and Williams (2019).[9]

The plan of the report is as follows. First, a brief timeline of the major events during the COVID-era that are germane to our analysis is provided. After that, the data and methodology are introduced, distinguishing between the simpler “traditional” indices and the more complex “advanced” indices. Then structural breaks are defined, with details on how to detect them econometrically. After that, the results are presented graphically, and various structural break tests are performed for each of the indices. Finally, implications of the results are discussed, followed by a conclusion.

COVID-19 Background

The swift policy responses to the economic impacts of COVID-19 began in March 2020, the first of which was a reduction in the target Federal Funds Rate on March 5, 2020, with a corresponding decrease on March 15, 2020. In addition, the U.S. Congress passed the Coronavirus Aid, Relief, and Economic Security (CARES) act on March 27, 2020, providing a number of relief benefits to American households, namely a pause on student loan payments and direct $1,200 payments to households.[10] These measures coincided with the declaration of a nationwide emergency and the designation of the COVID-19 disease as a pandemic on March 11 and 13, respectively, underlining the significance of March 2020 as the de facto start of the pandemic, or at least the start of its many policy responses.[11] This report focuses on the start of

[6] Admittedly, this report abstracts from interest rates in our analysis, which were at all-time lows in the period, presumably driving some demand, consequently affecting liquidity. Kuttner (2012) argues that “the impact of interest rates on house prices appears to be quite modest,” with a vector autoregression (VAR) model predicting a 10 basis point reduction in the long term interest rate leading to a home price increase of 0.3 percent to 0.8 percent, depending upon the level of the current interest rate. Future work could investigate the specific interest rate effect during the COVID era.

[7] For example, see Carrillo, de Wit, and Larson (2015) and Keys and Mulder (2020). The latter source notes that during the last financial crisis “the pattern of volume and prices during the housing market boom and bust demonstrates that prices are not a sufficient statistic for market demand, and that declines in volume may well occur before falling prices.” They then argue a similar pattern emerges due to a climate risk shock.

[8] See exhibit 15b.

[9] For other examples, van Dijk (2019) use a stochastic time trend (as opposed to a time fixed effect) to estimate TOM indexes in thin markets. Additionally, Genesove and Han (2012) develop a matching model to explain both buyer and seller TOM.

[10] Early in the pandemic, Cherry et al. (2021) found that the government and private relief induced more individuals into forbearance, about 25 percent, which suggests “large aggregate consequences for house prices and economic activity.”

[11] See the Center for Disease Control’s COVID-19 Timeline for a more detailed discussion of major events with regard to COVID-19.

COVID-19 as the initial shock. Exhibit 1 presents the events in the COVID-19 timeline that are germane for the analysis using information from the Centers for Disease Control and Prevention (CDC) and the World Health Organization (WHO).

Exhibit 1

Key COVID-19 Moments

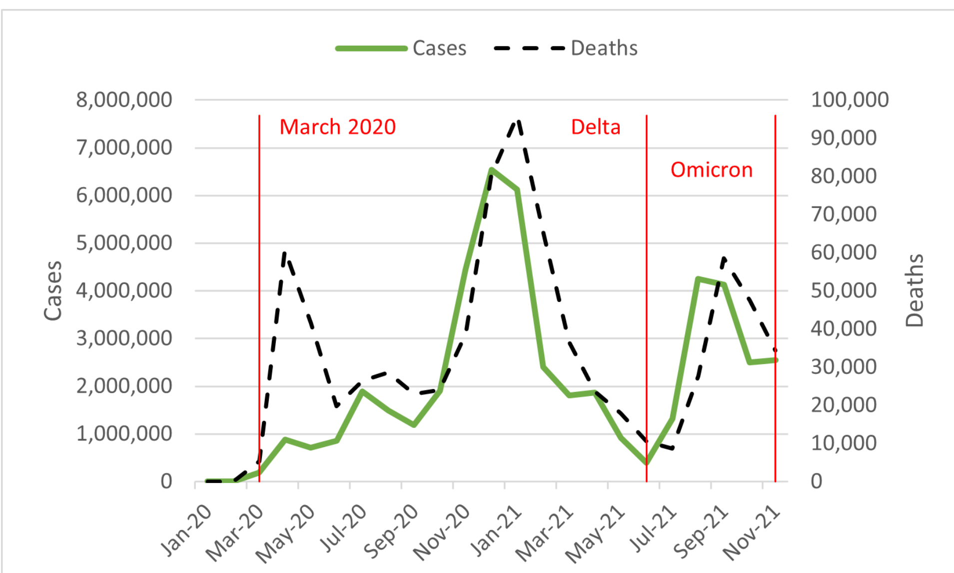
Date	Event
December 12, 2019	Patients in Wuhan, China experience symptoms
January 20, 2020	First confirmed case of COVID-19 in the United States
March 11, 2020	WHO declares COVID-19 a pandemic
March 13, 2020	President Trump declares a nationwide emergency
March 15, 2020	U.S. states begin to shut down to prevent the spread of COVID-19
June 1, 2021	Delta variant becomes the dominant variant in the U.S.
November 26, 2021	WHO classifies Omicron variant

Source: CDC (https://www.cdc.gov/museum/timeline/covid19.html)

Exhibit 2 shows actual case numbers and deaths from COVID-19 and its variants for the United States. Apart from an initial surge in deaths at the start of the pandemic in March 2020, the number of cases typically leads the number of deaths. After the pandemic was underway, the figure indicates an increase in the number of cases and deaths in the winter of 2021 and at the start of the Delta variant. One might expect the housing market responses to COVID-19 to be particularly strong during this period.

Exhibit 2

COVID-19 Cases and Deaths



Note: Data represent number of cases and deaths for each month reported at the national level.
Source: COVID-19 Data Repository by the Center for Systems Science and Engineering

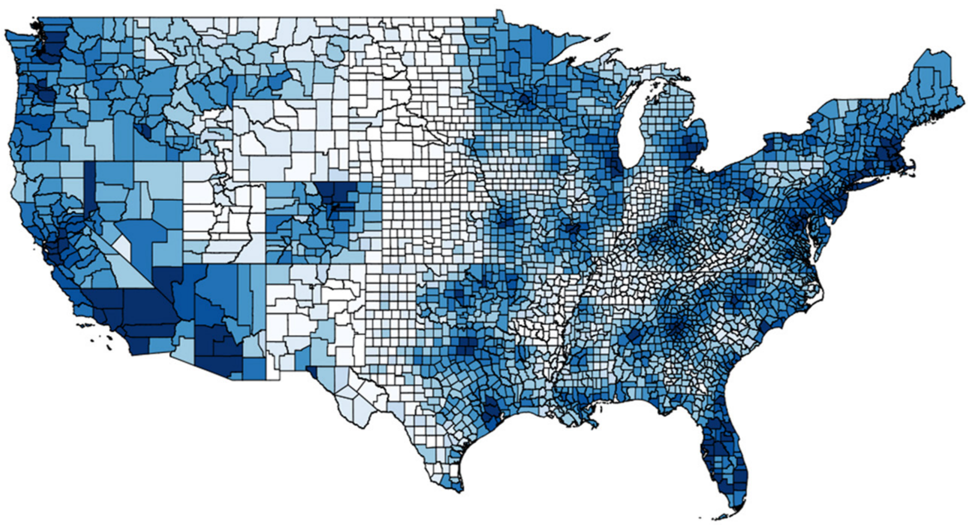
Data

The data come from CoreLogic, Inc. which provides listings data by combining data from 156 individual multiple listing services across the United States. A multiple listing service (MLS) is a regional database of property characteristics entered by the realtor including list date, contract date, list price, beds, baths, square footage, address, etc. According to the Real Estate Standards Organization (RESO), as of October 2020, around 80 percent of all homes sold are in an MLS system.[12]

The data span January 1980 through December 2021, though some regions have data from earlier periods. In the analysis, the focus is on the time period from January 2015 to December 2021. Data are sparse for counties in the west-north-central and south-west-central census divisions relative to the entire United States, whereas the middle-Atlantic and Pacific divisions comprise a large proportion of the listings in the data. Exhibit 3 shows coverage across the United States after culling for outliers.

Exhibit 3

Counties with Listings Between 2000–2021



Note: Data is presented after culling for outliers.
Source: Multiple Listings Service data provided by CoreLogic, Inc.

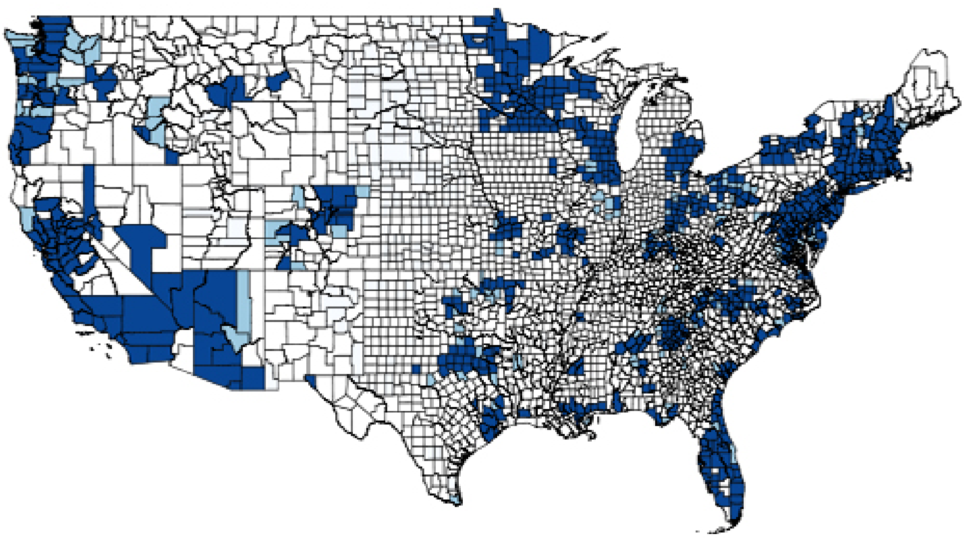
Outliers are removed if there are obvious data errors or other similarly impossible situations. Specifically, observations are dropped with negative or zero list or sale prices, missing addresses or state/county Federal Information Processing Standard (FIPS) codes, and missing close, contract, or off-market dates. Also, the bottom and top percentile of list prices for each year are dropped. Attention is restricted to single family residential homes, so that nonresidential properties, such as commercial real estate, farms, timeshares, etc., are also dropped. Additionally, nested listings, defined as listings with both a list date and contract or off-market date that falls within the same dates of

[12] See RESO (2020) for more information.

another listing for the same property, are removed.[13] Exhibit 4 illustrates the counties for which indices could be constructed for at least some time periods after removing outliers. Finally, since data were collected in December 2021, indices are omitted for that month for right-censoring reasons.[14]

Exhibit 4

Counties with Any Index, 2000–2021



Note: Filled in counties are those for which any index could be calculated, and darker counties are those for which an advanced index could be calculated.
Source: Multiple Listings Service data provided by CoreLogic, Inc.

Some care is needed in defining a listing, particularly when a home is relisted on the market shortly after being removed from the market. Following Carrillo and Williams (2019), two listings for a home are combined where the first listing did not end in a sale and the home was relisted within 60 days. This helps to address any potential strategic concerns of sellers who might withdraw properties and relist them to make the property appear to be a new listing or gain salience. The listing duration is then the sum of the individual listing durations. Note that this only applies to an unsold listing; the sale of a property always concludes a listing, regardless of when the property is listed next.

Housing Supply and Liquidity Indices

There is no single agreed-upon measure of either housing market supply or housing market liquidity. Different measures address different questions and have different purposes. In line with this logic, a suite of different indices is used, each of which has its own advantages and disadvantages. The measures of supply and liquidity are grouped into traditional measures

[13] For example, a home listed on June 1, 2020, and contracted on July 3, 2020, would qualify as a nested listing if that same property was also listed any time before June 1, 2020, with a contract or off-market date after July 3, 2020.

[14] Including the last month would likely mechanically estimate slower sale times because properties listed at the start of December may have simply not been on the market long enough to have had a chance to sell.

(typically summary statistics) and more advanced measures that are derived from econometric models. Each of the indices is a monthly index at the national level. Exhibit 5 lists all of the housing supply and liquidity indices that are calculated in this report, where the repeat proportional hazard index (RPHI) and the repeat median time on the market index (RMTI) are the advanced indices. Additionally, analysis is performed on home prices using the FHFA's HPI and its associated year-over-year (YoY) change.

Exhibit 5

List of Indices

Traditional Index	Description
Count of New Listings (logged)	Sum of listings listed in a particular month
YoY New Listings	Percent change in the count of new listings
Percent Sold 90 days	Proportion of total listings that sold within 90 days
Percent Sold 14 days	Proportion of total listings that sold with 14 days
Percent Withdrawn	Proportion of total listings that did not go on to sell
Percent of Price Drops	Proportion of total listings with sale price < list price
Mean TOM for sold listings (logged)	Average days between list and sale date for sold homes
Mean TOM for all listings (logged)	Average days between list and sale date or off-market date for all homes
Median TOM for sold listings (logged)	Median days between list and sale date for sold homes
Median TOM for all listings (logged)	Median days between list and sale date or off-market date for all homes
Advanced Index	**Description**
RPHI	Estimated using methodology of Carrillo and Williams (2019)
RMTI	Estimated using methodology of Carrillo and Williams (2019)

RPHI = repeat proportional hazard index. RMTI = repeat median TOM index. TOM = time on the market. YoY = year-over-year.
Notes: If a listing ended in a sale, it is considered sold. Otherwise, it is considered withdrawn. Withdrawn and unsold are used interchangeably.

The advanced measures are two indices developed by Carrillo and Williams (2019) that employ repeat sales techniques: the repeat proportional hazard index (RPHI) and the repeat median TOM index (RMTI). Coverage of the indices is expanded from a quarterly basis at the CBSA level for six different areas (Carrillo and Williams, 2019) to a monthly basis at the national level using 3,092 U.S. counties out of the 3,242 total U.S. counties and county equivalents.

Traditional Descriptive Indices

The mean and median TOM are common statistics used to measure the speed of sale of a typical home in a given housing market.[15] These measures are often interpreted as an indication of the level of housing market liquidity in a given time period. Generally speaking, lower values of TOM mean hotter markets (that is, relatively more buyers than sellers) because sellers can sell their properties relatively easily in a short amount of time. Some care is needed with terminology because TOM is typically defined only for sold listings, and the dates used may not be consistent across sources.[16] After grouping listings according to the process described previously, we define TOM for both sold

[15] For example, both Redfin and Realtor.com use median days on the market in their regular reports of housing markets.

[16] As Benefield and Hardin (2013) point out, even when considering only sold listings, there are different definitions of time on the market in the literature. For example, some papers use contract date as the termination date while others use closing date.

and unsold listings. For sold listings, TOM of a listing is defined as the number of days between the list date and the date the contract was signed. For unsold listings, TOM is defined as the number of days between the list date and the date the home was removed from the market. By comparing the mean (or median) TOM for sold and all (sold and unsold) listings, it is possible to analyze the consequences of censoring on these measures. Also, differences between mean and median give insights about the tails of the distribution of TOM.

To complement the typical measures of TOM, the fraction of homes sold with respect to three different time periods are considered: within 14 days, within 90 days, and with any number of days. The last measure is simply the percentage of homes that sell within a given list month. It is more convenient to work with its opposite, that is, the percentage of homes that were withdrawn from the market before selling. Analyzing the differences between the three indices can give additional information about how the distribution of TOM is changing.[17] For example, if the proportion of listings selling within 14 days increases, but the proportion of listings selling within 90 days and any number of days decreases, then the shape of the TOM distribution is changing, whereby mass is moved to the left of the distribution and the overall measure of sold homes is reduced. In other words, some homes experienced greater likelihoods of faster sales while the overall likelihood of a sale decreased.

A more direct measure of supply uses the number of new listings on the market.[18] For each list month, the count of new listings and its year-over-year percentage change are calculated. All else equal, the more new listings there are, the larger the supply of homes on the market. This will be the most direct measure of housing market supply.

The final traditional descriptive index is the percentage of homes listed each month that experience a price drop. This measure is defined only for sold listings. For the purposes of this report, a (sold) listing has experienced a price drop if the sale price is lower than the original list price. Notably this measure suffers from censoring in so far as price drops for unsold homes have different effects than price drops for listings that go on to sell. Nevertheless, the proportion of price drops gives insights into seller behavior. All else equal, the more price drops there are, the more likely buyers are to have bargaining power. Conversely, a drop in the number of price drops indicates a market with relatively limited supply.

To facilitate comparison with price trends, the Federal Housing Finance Agency's (FHFA) House Price Index (HPI)® and its year-over-year (YoY) appreciation rate are included in the traditional indices. Non-seasonally adjusted (NSA) values are used because the other series have not been seasonally adjusted.

While intuitive, the traditional measures tend to suffer from the well-known statistical problems of censoring and unobserved heterogeneity (across listings). Here the censoring problem manifests itself as homes being pulled off of the market before they have had a chance to sell. Thus, the

[17] For an example of work on the distribution of TOM, see Carrillo and Pope (2012), who extend the decomposition methods of DiNardo, Fortin, and Lemieux (1996) to analyze changes in the entire distribution of TOM in terms of changes in home characteristics versus changes in fundamental market conditions.

[18] Note that this excludes newly constructed homes that do not sell with a listing, as well as excludes home sales that are for sale by owner. This report cannot comment on these selection effects as we lack the sufficient data.

observed times on the market for sold homes are likely to be less than those for the entire population, leading to estimates of time on the market that are too small if only sold listings are used. Also, if sold listings are different from the population of listings in a systematic way, say possessing on average different housing characteristics, then traditional measures may be biased.[19]

The problem of unobserved heterogeneity for the traditional measures means not taking into account differences in the composition of homes that transact over time. If sold homes are not representative of the larger population, it is important to take into account these differences when measuring housing market performance.[20] For measures of house price appreciation, the hedonic and repeat sales approaches each offer a solution to this problem by attempting to control for the observable characteristics of the home and by differencing out any time-invariant characteristics between consecutive sales, respectively. Unobserved heterogeneity tends to plague hedonic methods (by definition) and repeat sales methods (at least to the extent that unobserved heterogeneity changes over time).

Fortunately, Carrillo and Williams (2019) develop two advanced measures of housing market liquidity that each handle both censoring and unobserved heterogeneity. Both measures exploit repeated sales of the same listing to difference out time-invariant unobserved features of a home that may influence its time on the market. These methods are data-intensive in that they require a home to be sold at least twice in order for it to be used for estimation. Fortunately, the data stretches far enough back in time to have a large number of usable observations.

Advanced Econometric Indices

The methodology behind the two advanced measures is now briefly introduced, where the reader can refer to Carrillo and Williams (2019) for further details. This report adopts their notation for expositional ease. The first advanced measure is a proportional hazard model called the RPHI.[21] The core assumption of this approach is that hazard rates are multiplicatively separable into a common term (usually called the baseline hazard) that varies over time, but is the same for all homes, and into an idiosyncratic term that varies by home but not over time.[22] Carrillo and Williams (2019) then marry this idea with a repeat sales methodology to "difference out" the idiosyncrasies for each home.

More formally, the hazard rate $\lambda_{it}(y)$ for home i at calendar date t that has already been on the market for y days is:

$$\lambda_{it}(y) = \exp(\beta_t) \times \exp(\alpha_i) \times \lambda_0(y) \tag{1}$$

[19] In a related vein for house price measurement, Gatzlaff and Haurin (1997), Gatzlaff and Haurin (1998), and Malone and Redfearn (2020) show that measures of house price appreciation from sold homes are likely to be biased using repeat sales, hedonic, and aggregation methodologies, respectively.

[20] For recent work in addressing changing composition with respect to home prices and home appreciation, see Contat and Larson (2022), who demonstrate the importance of changing geographic composition in index construction.

[21] See Cox (1972) for the seminal reference and Wooldridge (2002) for a more recent textbook treatment on proportional hazard models.

[22] In other words, the proportional hazard assumption maintains that if property A is twice as likely to sell as property B in the current time period, then A will always be twice as likely to sell as B in all future time periods, provided of course that both properties haven't yet sold at that time.

The $\lambda_0(y)$ term accounts for changes in the hazard rate due to how long the property has already been on the market and is common for all homes. The exp (α_i) term accounts for unobserved heterogeneity of home i, that is, the property-specific characteristics that do not change over time.[23] Finally, the exp (β_t) term accounts for changes in the hazard rate due to changing market conditions faced by all homes, akin to time-fixed effects in a linear regression. By differencing across consecutive listings, integrating, taking logs, and conditioning on a subset of the sample, one can estimate the original hazard formulation using the following logistic specification, where the coefficients β on the right-hand side below are the same as those given in (1):

$$\Pr(V_i^2 \geq V_i^1 | W_i = 1) = \frac{\exp(\beta_{t_i^1})}{\exp\left(\beta_{t_i^1}\right) + \exp(\beta_{t_i^2})} \tag{2}$$

Here $V_i^s = \min\{Y_i^s, C_i^s\}$ is the minimum of the time on the market Y_i^s (observed only for sold homes) and the censoring time C_i^s (observed if home did not sell and was pulled off market) for property i for its sth-listing. Note that V_i^s is always observed.[24] The superscripts $s = 1, 2$ indicate the sequential number of the listing, so that, for example, $\beta_{t_i^2}$) represents the coefficient for the time at which home i was listed for the second time in a pair of repeat listings. The conditioning variable W_i is equal to 1 if either (a) both the first and second listings sold, or (b) if one of the listings sold and its time on the market is shorter than the censored time for the other (unsold) listing. In this way one can estimate the RPHI μ_t = exp (β_t) for time t using a logistic regression on a particular subsample of data, where the explanatory variables indicate the times of sales.

The second advanced measure is the RMTI. The strategy with this index is that if the median time on the market is stationary (conditional on any differences due to listing period), then one can start with:

$$\log(Y_i^t) = \beta_t + \alpha_i + \epsilon_{it} \tag{3}$$

and then take medians and differences to get:

$$Med(\log(Y_i^2) | X_i) - Med(\log(Y_i^1) | X_i) = \beta X_i \tag{4}$$

As before, the unobserved heterogeneity α_i term has been successfully differenced out, a step that requires repeated sales of the same home. The idea is that roughly the difference step takes care of the unobserved heterogeneity, whereas the median step takes care of the censoring. The right-hand side β coefficients of (4) are the same as those of (3), allowing estimation of the RMTI.

Unlike the RPHI, higher values of the RMTI imply that a home is likely to spend a longer time on the market, all else equal. As such, this report follows Carrillo and Williams (2019) and uses the inverse of the RMTI for easy comparison with the RPHI. In this way both the RPHI and inverse RMTI are positive measures of home liquidity, so that higher values of these indices mean that homes are likely to sell faster.

[23] Accounting for unobserved heterogeneity that changes over time is well beyond the scope of this article.

[24] If the listing sold then $V_i^s = Y_i^s$, while if the listing did not sell $V_i^s = C_i^s$.

Structural Breaks

To complement visual inspection of the graphs and to provide more rigorous analysis, for each index a test for structural breaks in two different models is run. Each model allows for different types of structural change that could have taken place due to the COVID-19 pandemic. One addresses possible nonstationarity using a deterministic time trend, whereas the other uses a stochastic time trend in the form of an auto-regressive (AR) process. Specifically, the first model uses a linear time trend and seasonal effects to test for breaks in the intercept, slope, and seasonality in each index. To use more standard methodology, a second model is introduced, which is the preferred model. The second model uses an auto-regressive process of order two (that is, AR(2) process) with seasonal effects to test whether COVID-19 had transient effects or were permanent, as well as tests for breaks in seasonality.

Before estimating an index, a Dickey-Fuller test is performed to detect the presence of a unit root. Results for these tests are located in the last column of exhibit 6. If the tests suggest the series has a unit root, the series is differenced and adjust our specification accordingly before performing estimation. Additionally, for count variables, mean TOM, and median TOM, index is converted into log terms to deal with possible heteroskedasticity.

Exhibit 6

Single Structural Breaks for Time Series

Traditional Index	Linear Model			AR(2)		Unit Root
	Break at March 2020?	Suggested Break	Type of Break(s) ♠	Break at March 2020?	Type of Break(s) ♠	
Count of New Listings (logged) §	✓	Sept 2020	L,M	✗	-	✗
YoY New Listings♦	✗	May 2020*	-	✓	-	✓
Percent Sold 90 days	✓	April 2020	L,M	✗	-	✗
Percent Sold 14 days	✓	May 2020	L,M,S	✓	M	✓
Percent Withdrawn	✓	July 2020	L,M,S	✗	S	✓
Percent of Price Drops	✓	June 2020	L,M,S	✓	L,M,S	✓
Mean TOM for sold listings (logged)	✓	Dec 2019	L,M,S	✗	-	✓
Mean TOM for all listings (logged)	✓	Nov 2019	L,M,S	✓	M	✓
Median TOM for sold listings (logged)	✓	May 2020	L,M,S	✓	S	✓
Median TOM for all listings (logged)	✓	Nov 2019	L,M,S	✓	M	✓
Advanced Index						
Repeat Proportional Hazard	✓	Dec 2019	L,M,S	✓	L,M,S	✓
Inverse Repeat Median TOM	✓	Sept 2020	L,M,S	✓	M,S	✓
House Prices						
FHFA Purchase HPI (NSA)	✓	June 2020	L,M,S	✓	M,S	✓
YoY FHFA Purchase HPI (NSA)	✓	Sept 2020	L,M,S	✗	S	✓

*AR = auto-regressive. FHFA = Federal Housing Finance Agency. HPI = House Price Index. TOM = time on the market. YoY = year-over-year. L = shift in intercept. M = shift in slope. S = shift in seasonal effects. *Suggested break is not statistically insignificant. ♦ The difference in logs was used instead of the usual percent change formula. § Depending upon the specific F-test, the series breaks at March 2020 with marginal statistical significance slightly below or above the 95% level. ♠ The types of breaks were determined using the estimation at the suggested break date listed in this table.*

Notes: Types of breaks always refer to the series estimated, and not necessarily of the base level series. Logs of series were used where indicated in parentheses.

Source: Multiple Listings Service data provided by CoreLogic

Linear Time Trend with Seasonal Effects

Let y_t be the index in question. A simple model relates y_t linearly to time t and includes seasonal effects m_t.[25] If y_t has a unit root, then the difference $\Delta y_t = y_t - y_{t-1}$ should be used in its place. To test for a structural break at time t_0 one could use the following model:

$$z_t = \beta_0 + \beta_1 t + \beta_2 1_{t>t_0} + \beta_3(1_{t>t_0} \times t) + m_t + n_t 1_{t>t_0} + \epsilon_t \quad (5)$$

where $z_t = y_t$ if y_t does not have a unit root and $z_t = \Delta y_t$ if y_t has a unit root. Here $1_{t>t_0}$ is an indicator variable equal to one if $t>t_0$ and zero otherwise. In this setting, t_0 corresponds to the start of COVID-19 (March 2020). Without a unit root, the coefficients β_2 and β_3 represent changes in the intercept and slope of the index, respectively, holding seasonal effects constant. With a unit root, β_2 and β_3 represent changes in the intercept and slope of the difference of the index, which one could interpret as change in the slope and rate of increase in the slope of the original level series y_t. Seasonal fixed effects are also allowed to change at the break date t_0, where m_t and $m_t + n_t$ are the seasonal fixed effects before and after t_0, respectively.[26] One can interpret changes in the seasonal effects, represented by n_t, as changes in seasonality induced by COVID-19.

Running a statistical test on the joint hypothesis H_0: $\beta_2 = \beta_3 = 0$ would then help provide evidence for whether or not a different time trend occurred after the start of COVID-19, holding fixed the seasonal effects. To test this hypothesis, a Likelihood Ratio (LR) test is performed.[27] To test for changes in seasonality, a joint F-test on the vector of changes in seasonal fixed effects is used: $H_0 : n_t = 0$. Of course, one can test for any change in coefficients using H_0: $\beta_2 = \beta_3 = n_t = 0$.

In addition to testing for a structural break at a specific time (March 2020), the most likely time for a structural break for each series is estimated using the supremum of all the test statistics at each month. In other words, the time where the test statistic is the largest is used to determine where the break is most likely to occur. In order to minimize false positives, this approach adjusts the critical value to account for the fact that the break date is not known in advance.[28] Fortunately, as Andrews (1993) points out, this supremum test is valid even if the underlying series is nonstationary under a null hypothesis of parameter stability.

After determining the most likely break date econometrically, referred to as the suggested break date in exhibit 6, breaks which are present at the suggested break date are identified. For the linear time trend model, a change in the level value of the index occurs if the intercept (that is, constant) has changed, which in the model is a statistically significant β_2. Similarly, there was a change in the growth or slope of the index if β_3 is statistically significant. Finally, there was a structural break in seasonality if n_t is statistically significant.

[25] More advanced methodologies might employ multiple structural breaks, multiple covariates, and allow partial breaks (that is, a change in the coefficients of some but not all variables). See Bai and Perron (2003) for a review of such methodology, and Knoll, Schularick, and Steger (2017) for a recent application with home prices.

[26] Spring is defined as March–May, summer as June–August, fall as September–November, and winter as December–February.

[27] While it is well known that the Likelihood Ratio (LR), Wald, and Lagrange (that is, "slope") tests are all asymptotically equivalent, in smaller samples they may lead to different conclusions (Wooldridge, 2002). Given the time series framework, this may be particularly germane, so the LR test is used.

[28] See Davies (1987) for a seminal reference, Hansen (2001) for a quick introduction, and Perron (2007) for more recent surveys on the econometrics of structural breaks.

AR(2) Process with Seasonal Effects

The second model is a more traditional time series model. Each index follows an auto-regressive process of order 2, that is, AR(2). Some care is needed in interpreting the coefficients in the model because some indices were differenced before estimation to account for unit roots. Thus, for series without unit roots level index y_t is used as the dependent variable, whereas for series with unit roots the difference is used as the dependent variable. More formally, the second model is:

$$z_t = \beta_0 + \beta_1 z_{t-1} + \beta_2 z_{t-2} + m_t + n_t 1_{t>t_0} + \alpha_1 1_{t=t_0} + \alpha_2 1_{t>t_0} + \epsilon_t \quad (6)$$

where again $z_t = y_t$ if y_t does not have a unit root and $z_t = \Delta y_t$ if y_t has a unit root.

For series without unit roots, the interpretation of coefficients is straightforward. The α_1 term captures a temporary shock in the level of the index, whereas the α_2 term captures a persistent shock in the level of the index. A temporary shock would decay in the usual fashion as a consequence of the auto-regressive process. In contrast, a persistent and permanent shock effectively shifts the constant in the regression. If y_t is stationary, then it is easy to show that shifts in the constant are associated with shifts in the expected value $E[y_t]$, so that α_1 and α_2 capture changes to the expected value of the index. Finally, as before the n_t parameters represent changes to the seasonal fixed effects.

For series with unit roots that have been differenced, the interpretation of the coefficients is slightly changed. Now α_1 represents a one-time increase in the difference of y_t, which is equivalent to a permanent increase in the level of y_t. Also, α_2 represents a permanent increase in the difference of y_t, which is equivalent to a permanent increase in the slope of y_t. Finally, n_t represents a permanent change to seasonal effects for the difference of y_t, which is equivalent to a change above the expected change in seasonal coefficients.

One can test for structural breaks with H_0: $\alpha_1 = \alpha_2 = 0$ using an F-test. Additionally, as before, non-zero values of n_t provide further evidence of structural changes. A test for such structural changes uses H_0: $n_t = 0$. Exhibit 6 indicates if there is evidence of either break at March 2020. Then, using the suggested break date from the linear trend model, a test for the specific types of breaks using the previously suggested F-tests at that suggested break date for each index is performed.

Results and Discussion

In the data, we say that a listing is sold if it has a close price and either a close date or contract date. Otherwise, we say that the listing is unsold. As mentioned previously, this classification poses problems only at the end of the sample, where a property might have been listed too closely to the data collection time for either the listing to have been removed or to have been sold. To address this concern, index values for the last month in our sample are not reported. Exhibit 6 summarizes the results for structural breaks for each of our two models. Exhibit 7 lists all the specific parameter estimates at the suggested break dates for each of the two models.

Exhibit 7

Model Estimates

Traditional Index	Linear Time Trend Model: Intercept	Linear Time Trend Model: Slope	Linear Time Trend Model: Intercept Break*	Linear Time Trend Model: Slope Break*	AR(2) Model: Transitory	AR(2) Model: Permanent Shock
Count of New Listings (logged)	12.39*** (0.60)	-0.00 (0.00)	22.35** (8.15)	-0.03** (0.01)	0.10 (0.13)	0.02 (0.09)
YoY New Listings	0.30 (0.79)	-0.00 (0.00)	7.94 (5.90)	-0.01 (0.01)	0.44 (0.31)	-0.02 (0.06)
Percent Sold 90 days	0.08 (0.12)	0.00*** (0.00)	13.60*** (0.79)	-0.02*** (0.00)	0.04* (0.02)	0.05 (0.04)
Percent Sold 14 days	-0.17 (0.12)	0.00** (0.00)	5.47*** (0.91)	-0.01*** (0.00)	0.04 (0.11)	-0.03** (0.01)
Percent Withdrawn	0.34*** (0.07)	-0.00* (0.00)	-20.30*** (0.64)	0.03*** (0.00)	-0.01 (0.01)	0.02 (0.01)
Percent of Price Drops	1.20*** (0.07)	-0.00*** (0.00)	11.24*** (0.55)	-0.02*** (0.00)	-0.04*** (0.01)	-0.03*** (0.00)
Mean TOM for sold listings (logged)	5.23*** (0.49)	-0.00 (0.00)	47.28*** (2.46)	-0.7*** (0.00)	-0.01 (0.12)	-0.11 (0.09)
Mean TOM for all listings (logged)	5.11*** (0.33)	-0.00 (0.00)	46.13*** (1.54)	-0.06*** (0.00)	0.02 (0.37)	-0.04* (0.02)
Median TOM for sold listings (logged)	5.85 (0.65)	-0.00** (0.00)	30.53*** (4.94)	-0.04*** (0.01)	-0.27 (0.56)	0.09 (0.05)
Median TOM for all listings (logged)	5.11*** (0.33)	-0.00 (0.00)	46.13*** (1.54)	-0.06*** (0.00)	0.02 (0.37)	-0.04* (0.02)
Advanced Index						
Repeat Proportional Hazard	3.31*** (0.64)	-0.00** (0.00)	-70.83*** (3.20)	0.10*** (0.00)	-0.26*** (0.06)	0.22*** (0.03)
Inverse Repeat Median TOM	5.75*** (0.45)	-0.01*** (0.00)	-119.92 (6.10)	0.17*** (0.01)	-0.09 (0.09)	0.23*** (0.04)
House Prices						
FHFA Purchase HPI (NSA)	-580.57*** (6.21)	1.19*** (0.01)	-2,473.2*** (52.08)	3.41*** (0.07)	2.03 (3.02)	2.22*** (0.33)
YoY FHFA Purchase HPI (NSA)	-3.33 (3.28)	0.01** (0.00)	-410.17*** (44.24)	0.57*** (0.06)	0.33 (0.71)	0.23 (1.02)

*AR = auto-regressive. FHFA = Federal Housing Finance Agency. HPI = House Price Index. TOM = time on the market. YoY = year-over-year. *p < 0.05. **p < 0.01. ***p < 0.001.*

Notes: Estimation performed at estimated break dates listed in exhibit 6. Standard errors given in parentheses.

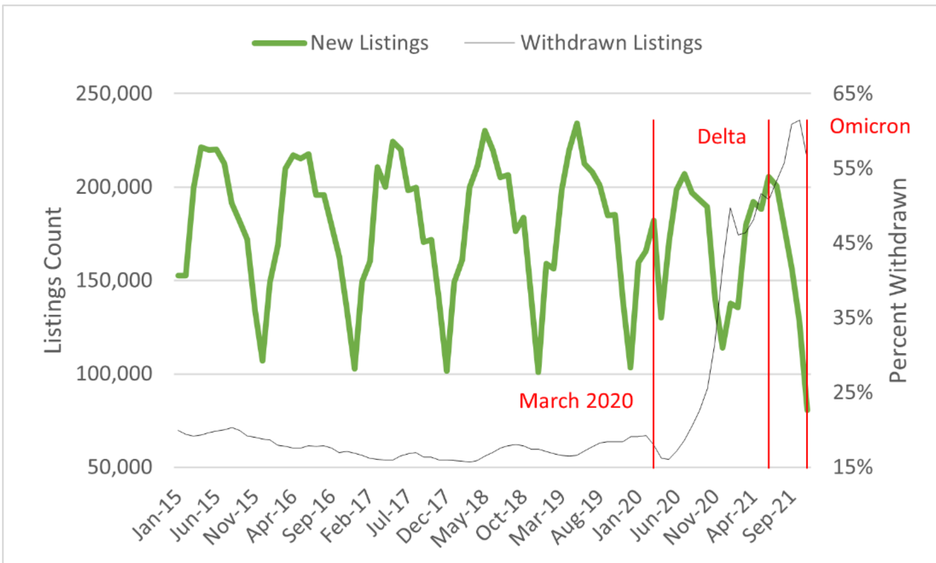
Source: Multiple Listings Service data provided by CoreLogic

Traditional Index Analysis

Exhibit 8 illustrates the trend of new listings over time. As evident from the graph, there are strong seasonal patterns for new listings. Additionally, there is evidence of a general reduction in the number of new listings starting March 2020. Due to strong seasonal effects and the linear time specification, t is no surprise that no evidence of a structural break is found in exhibit 6. To better identify changes in trend for new listings, year-over-year changes can be used, where in principle seasonal effects should cancel themselves out.

Exhibit 8

New Listings, 2015–2021



Note: Data are estimated at the national level.
Source: Multiple Listings Service data provided by CoreLogic

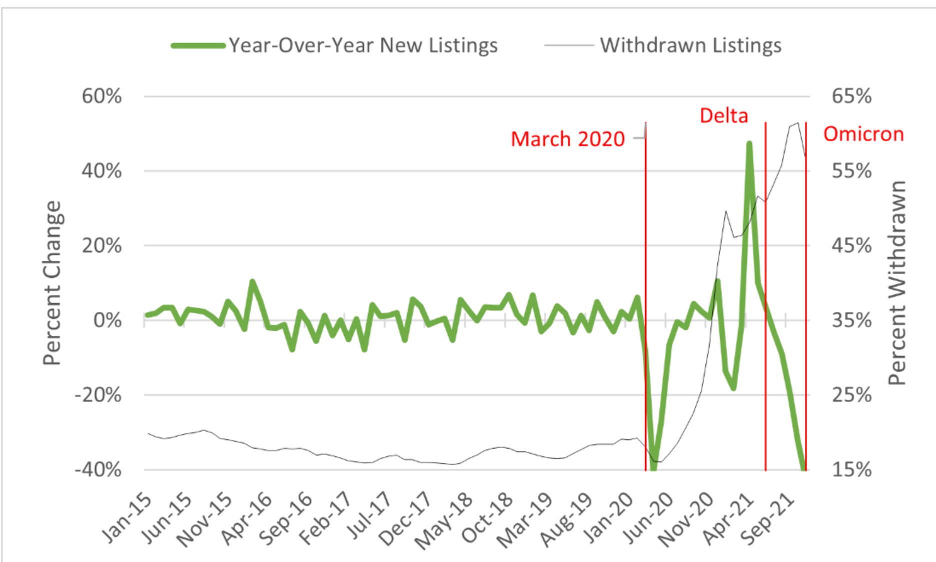
Exhibit 9 illustrates the year-over-year percent change in new listings which shows changes in the trend for the start of the pandemic, the Delta variant, and the Omicron variant. A clear decrease at the start of COVID-19 in March 2020 and also for the Delta variant around April 2021 are evident. There also appears to be a drop corresponding to the Omicron variant around November 2021, though this appears too close to the end of the sample to make any definitive statements.

There is no strong evidence of a structural break for either the count of new listings or the year-over-year new listings in either of our two specifications. For the latter, this is likely due to the sharp partial recovery afterwards, which is not modeled. Nonetheless, the graphs suggest that the supply of homes on the market available for sale was disrupted by COVID-19. To further investigate, the number of listings before and after March 2020 for 12- and 21-month windows is calculated. For the 12-month window there is, on average, a 15,000 decrease in the number of new listings, whereas for the 21-month window there is a 22,000 decrease in new listings. Alternatively, the peak of new listings decreased by roughly 28,000, or about 12 percent, from the pre-COVID-19 average to the post-COVID-19 average. Future work could use more sophisticated time series approaches to formally model the shocks and recoveries that mechanically show up in the seasonal year-over-year series.

Exhibits 8 and 9 also illustrate the percent of withdrawn listings. Prior to COVID-19, the percentage of withdrawn listings was relatively stable around 16 percent. However, graphically there is evidence that around April 2020 there was a sharp increase in the percentage of homes that did not sell. As the reference lines indicate, there was a dramatic and sustained increase from around April 2020 to January 2021. During this time period the percentage increased (approximately) from 15 percent to over 45 percent, so that the proportion more than tripled. Structural Break tests indicate that the most likely break occurred several months later in July 2020. There is mixed evidence of breaks in the two models. The linear model suggests intercept, slope, and seasonal breaks, whereas the AR(2) finds only small evidence of seasonal shocks. Though some of the increase in the percentage of withdrawn listings at the end of our sample is likely due to data collection censoring as previously mentioned (even after discarding the last month's observations), there is still a large increase in the percentage of withdrawn listings, except in the last month. Indeed, in November 2021 there was actually a decrease in the percentage of withdrawn listings. This provides some evidence of an increase in the probability of a home selling at the end of the data sample because this more than compensates for the mechanical increase in withdrawn percentage due to censoring.

Exhibit 9

Withdrawn Listings, 2015–2021

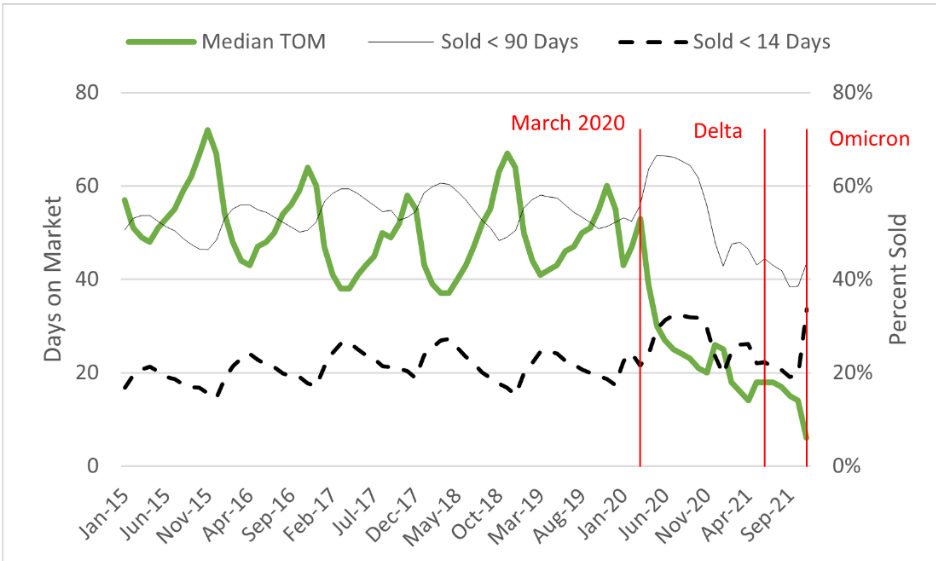


Note: Data are estimated at the national level.
Source: Multiple Listings Service data provided by CoreLogic

Exhibit 10 illustrates the proportion of listings sold within 14 and 90 days in the 2015–21 time period. Note that the proportion of very fast sales, that is, within 14 days, increased at the start of COVID and did not return to similar values seen before COVID until well into the pandemic around the end of the sample in December 2021. In contrast, the percent sold within 90 days experienced a brief increase (likely due to an increase in homes that sold very fast), but then experienced lower levels relative to prepandemic values. Coupled with the fact that the percentage of withdrawn listings (that is, sold within any number of days in the sample) increased in the sample indicates a change in the distribution of TOM. Indeed, as exhibit 11 indicates, the pre-COVID and post-COVID periods saw a first-order stochastic shift in time on the market, where homes across the distribution are likely to sell faster in the post-COVID period. Though it is not shown in this report, using a 21-month window instead of a 12-month window leads to a very similar graph.

Exhibit 10

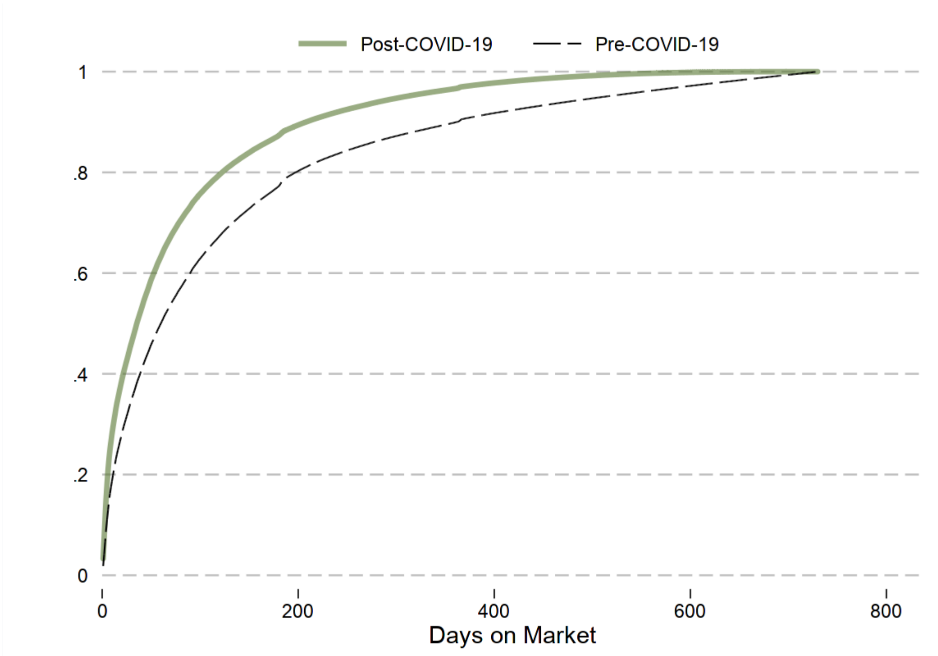
Median TOM and Speed of Sale, 2015–2021



TOM = time on the market.
Note: Data are estimated at the national level.
Source: Multiple Listings Service data provided by CoreLogic

Exhibit 11

Cumulative Distribution of Time-on-Market Pre- and Post-COVID-19, 12-month Window



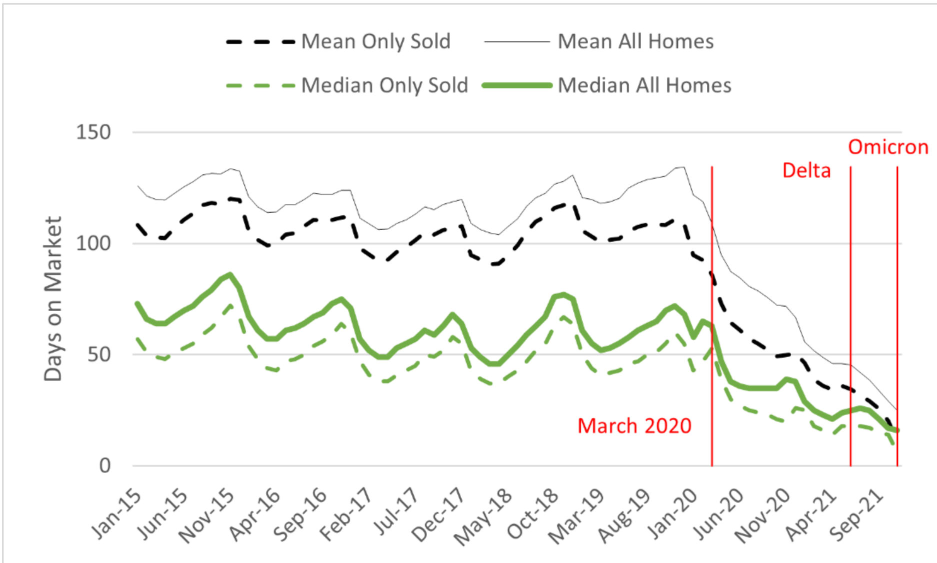
Notes: Data are estimated at the national level. Pre- and Post-COVID denotes the designated number of months before or after March 2020. For the 12-month window, the pre-COVID-19 period consists of February 2019 through February 2020 and the Post-COVID period consists of March 2020 through March 2021. Picture was very similar using a 21-month window, with even more of a pronounced difference.

Source: Multiple Listings Service data provided by CoreLogic

Exhibit 12 illustrates both the mean and median TOM during the sample period. Note that the mean tends to be greater than the median for both sold and all listings, indicating that the distribution of TOM is relatively right skewed. In other words, the homes that stay on the market the longest do so for disproportionately long times. Additionally, in agreement with Carrillo and Williams (2019), there is evidence of the consequences of censoring in that sold and unsold metrics lead to different index values, where TOM for sold homes is smaller (on average) than the TOM for all homes listed on the market. The changes in trends across both mean and median, as well as sold and unsold, appear very similar, so that a decrease (increase) in one index is followed by a proportional decrease (increase) in the other.

Exhibit 12

Time-on-Market, 2015–2021



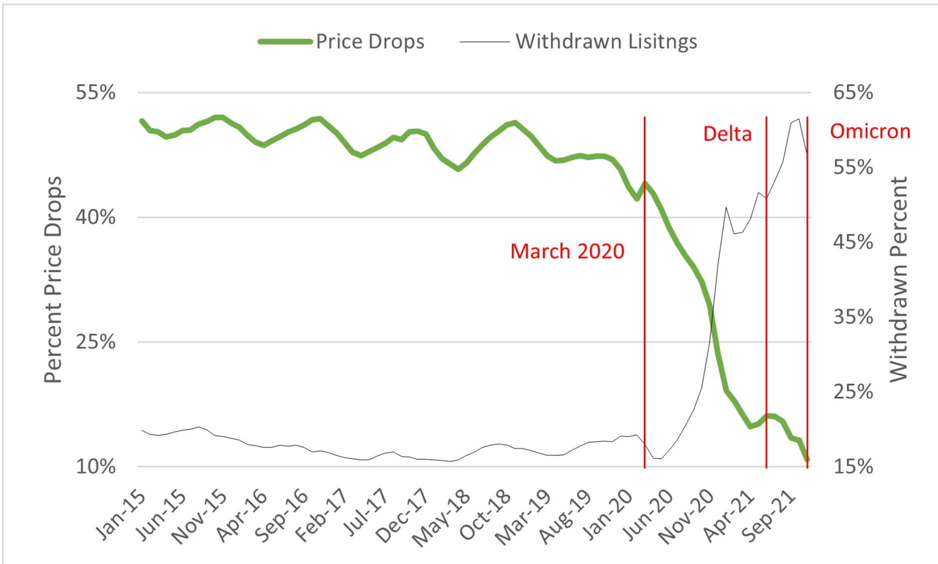
Note: Data are estimated at the national level.
Source: Multiple Listings Service data provided by CoreLogic

Exhibit 12 also indicates a downturn in mean and median TOM starting around March 2020 that has yet to recover, at least as of the last month in the sample (November 2022). For both sold and all listings' median TOM, graphically there is evidence of a structural break at March 2020, though the structural breaks test give different results. This is likely because the difference of logged mean/median TOM was used, rather than the raw series. Nonetheless, except for logged median TOM, which has a later suggested break point, all of the evidence points to a break in TOM indices around November and December of 2019, where, to be clear, the date corresponds to the month in which the property was listed. In other words, the effects of COVID on shorter selling times were first felt by properties listed at the very end of 2019. For a ballpark comparison, for the period January 2015 to December 2019, the mean and median TOM for sold listings were 119 and 63 days, respectively. For properties listed in November 2019, this would correspond to a sale date around March and January of 2022, respectively.

Exhibit 13 illustrates the percentage of price drops in the 2015–21 period. As with median TOM, there is evidence of a sharp decrease in this index around March 2020. Structural break tests suggest that the break occurred later in June 2020. There is strong evidence of all types of structural breaks, indicating a clear break in selling behavior regarding changing price. In short, sellers were unambiguously less likely to reduce prices after the start of the pandemic.

Exhibit 13

Withdrawn Listings and Price Drops, 2015–2021



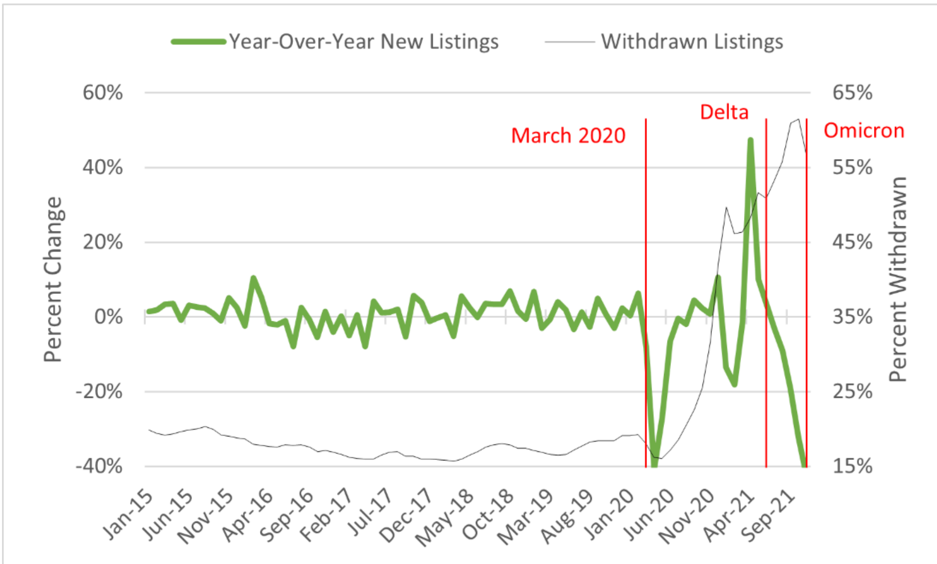
Note: Data are estimated at the national level.
Source: Multiple Listings Service data provided by CoreLogic

Finally, to complement the supply and liquidity indices two price-related indices were also analyzed. The first is FHFA's monthly national (purchase-only) HPI, non-seasonally adjusted.[29] Exhibits 14 through 17 graph changes in price levels and appreciation against other traditional indices. There is evidence of a sharp increase in price appreciation at the start of the COVID-19 pandemic in March 2020, though the structural break test indicates that the structural break likely first occurred later in June 2020. Surprisingly the results show that the percentage of withdrawn listings and year-over-year HPI appear to be highly correlated, as evident from exhibit 15. Exhibit 13 shows that the number of homes with price drops, that is, where the property sold for a price lower than the list price, decreased sharply at the start of COVID-19, in tandem with the increase in withdrawn listings. Graphically, the trend in YoY price appears to be negatively related to both mean and median TOM. Apart from the YoY AR(2) model, which finds limited evidence of a seasonal structural break, the results suggest there may have been a break in trend and also in seasonal effect in home prices, both in levels and appreciation.

[29] The non-seasonally adjusted version of the index is used for ease of comparison with the other indices, which are also not seasonally adjusted.

Exhibit 14

Change in New Listings and YoY HPI, 2015–2021

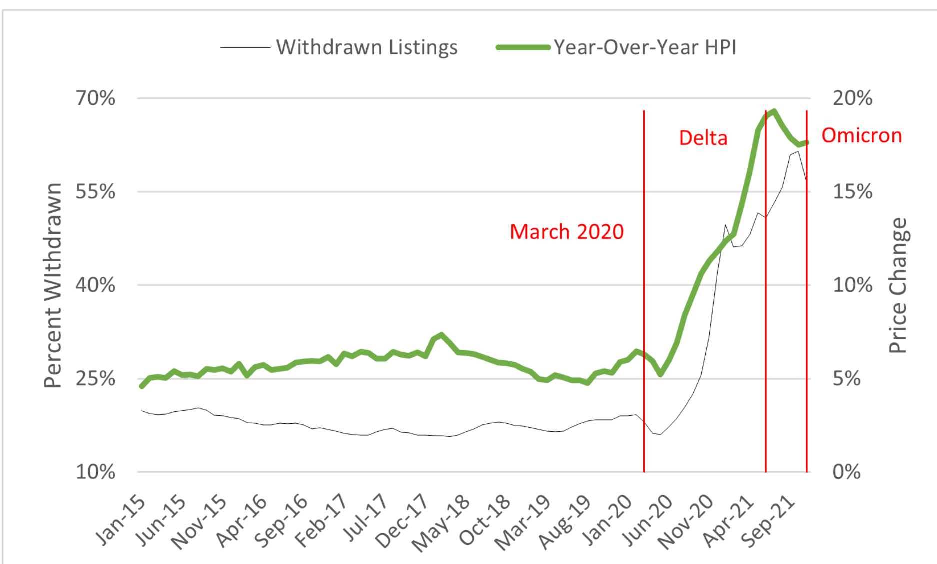


Note: Data are estimated at the national level.

Sources: Multiple Listings Service data provided by CoreLogic, Inc. and FHFA HPI® (purchase-only, not seasonally adjusted)

Exhibit 15

Withdrawn Listings and HPI, 2015–2021

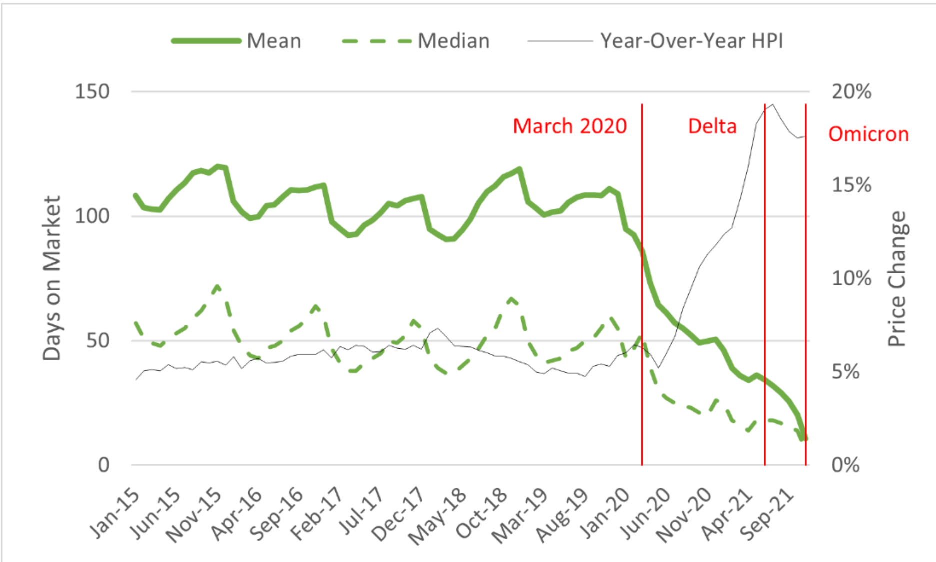


Note: Data are estimated at the national level.

Sources: Multiple Listings Service data provided by CoreLogic, Inc. and FHFA HPI® (purchase-only, not seasonally adjusted)

Exhibit 16

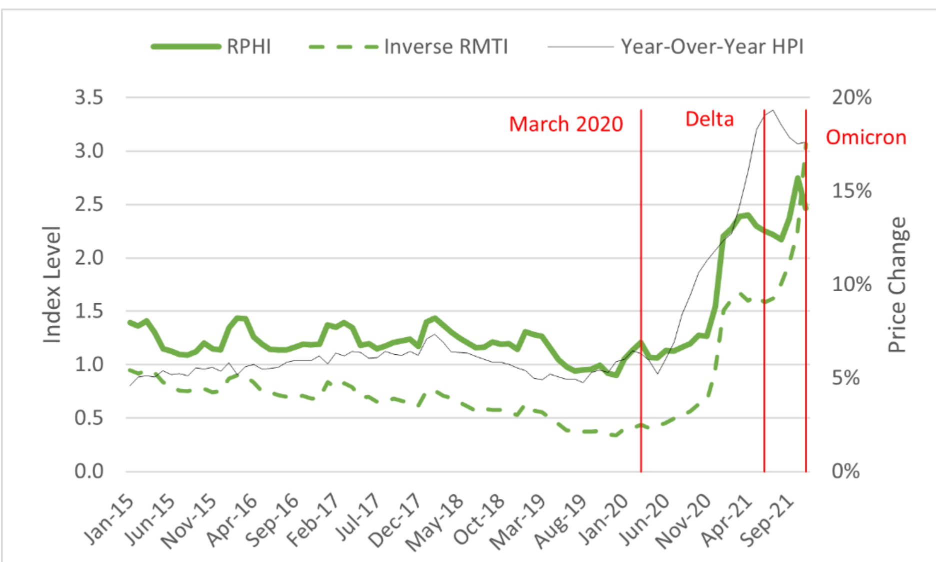
TOM Liquidity, and House Prices, 2015–2021



Note: Data are estimated at the national level.
Sources: Multiple Listings Service data provided by CoreLogic and FHFA HPI® (purchase-only, not seasonally adjusted)

Exhibit 17

Advanced Liquidity Measures and House Prices, 2015–2021



HPI = House Price Index. RMTI = repeat median TOM index.
Note: Data are estimated at the national level.
Sources: Multiple Listings Service data provided by CoreLogic and FHFA HPI® (purchase-only, not seasonally adjusted)

In summary, the traditional indices paint a relatively straightforward picture. At the start of the pandemic, new listings decreased and price appreciation started to climb quite quickly. Both mean and median time on the market started falling because homes were being sold in shorter times. However, this needs to be qualified with the fact that the proportion of listings that did not sell increased from around 15 percent to around 60 percent at its peak. While seemingly counterintuitive, one possible reason could be a shortage of supply. Home sellers often are home buyers as well. A homeowner may choose to delay a transaction until he or she has secured a future home in which to live. This could be reflected in the data as a seller whose listing is on the market but does not exit the market. The fact that the proportion of listings sold within a very quick timeframe (14 days) saw a large increase before resuming to previous levels could be due either to waiting on a home purchase or sellers seeing rapid price appreciation and deciding to hold out for very high prices. Future research could determine the exact mechanism.

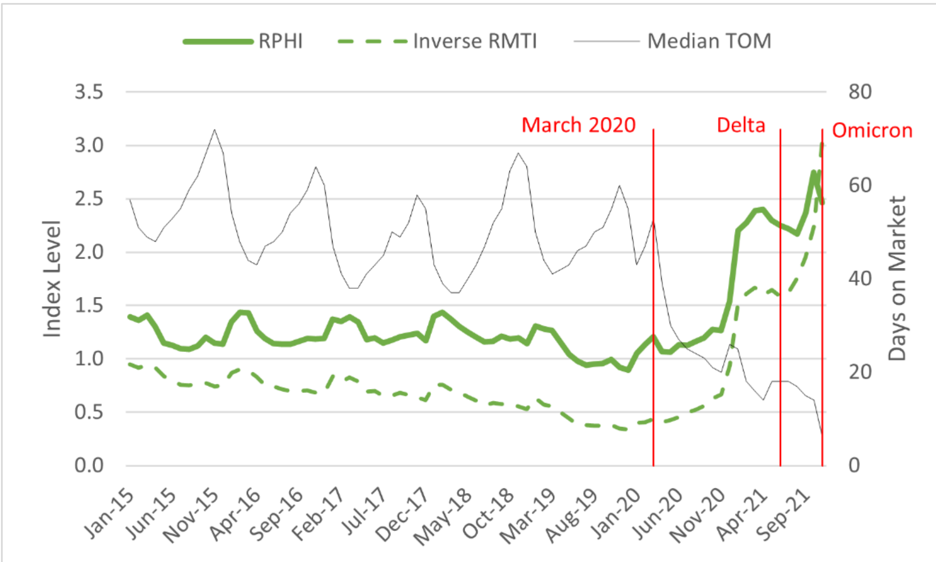
Advanced Index Analysis

Exhibit 18 illustrates the differences between the inverse RMTI and the median TOM. One would expect them to be inverses to some extent, on the one hand, since the RMTI is at its core a measure of the median TOM. However, the indices are not perfectly inversely related, suggesting that the RMTI's correction for censoring and unobserved heterogeneity is not without warrant. Exhibit 18 shows that the break in the (inverse) RMTI did not occur until much later, around December 2020, when there was a sharp increase. Moreover, the sharp increase was sustained for a few months before the RMTI flattened, only to experience another sharp increase shortly after the introduction of the Delta variant in June 2021.

Exhibit 18 also shows the RPHI and RMTI during the sample period. Both experienced similarly sized shocks at similar times. Both were relatively flat until December 2020, when there then was a sharp sustained increased. This increase was followed by another relatively flat period until July 2021 for the RMTI and August 2021 for the RPHI, when the index started increasing again. Hence, although the RPHI and RMTI have different methodologies, they may be close substitutes in practice. The one difference is that exhibit 18 suggests that the RPHI is flatter over time, but the RMTI seems to vary more over time. Structural break tests suggest a later break date of September 2020 for the inverse RMTI and an earlier break date of December 2019 for the RPHI. These differing results could point out a need to incorporate a more advanced time series analysis that can handle multiple structural breaks. This is discussed more in the conclusion. Nonetheless, there is strong evidence of all types of structural breaks for the advanced indices.

Exhibit 18

Advanced Measures of Time-on-Market, 2015–2021



RMTI = repeat median TOM index. RPHI = repeat proportional hazard index. TOM = time on the market.

Notes: The inverse RMTI is used here to more closely compare with results of the RPHI. Both are measured at the national level. Here, median time-on-market is estimated for only sold homes.

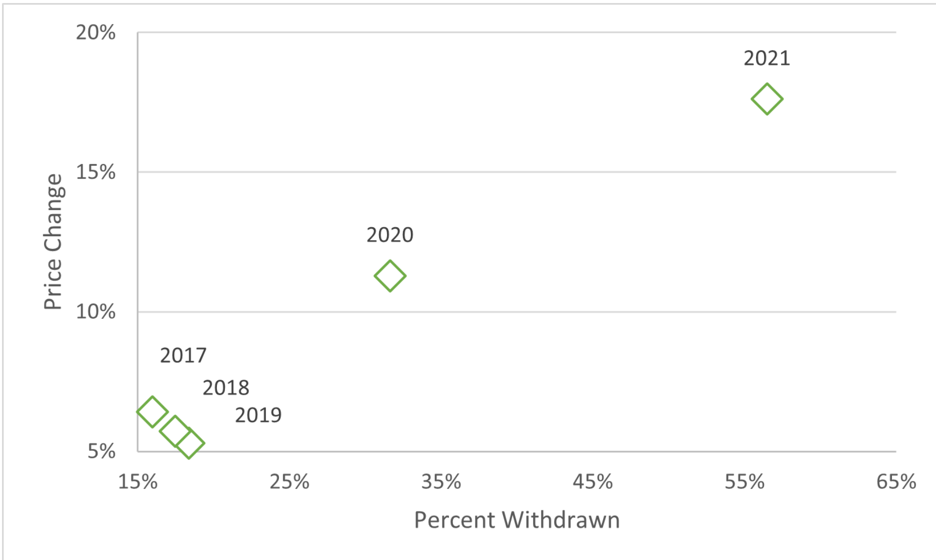
Source: Multiple Listings Service data provided by CoreLogic

Discussion

The breaks in the indices paint a clear picture of the housing market in the COVID-19 era. At the start of the pandemic (March 2020), there was a decrease in new listings, thus decreasing the supply on the market. Eventually, in the summer of 2020, listings started to increase, though not to their pre-COVID levels. This decrease in supply coincided with a sharp increase in price appreciation. Thus, there is evidence that the surge in prices due to COVID-19 was at least partially driven by a lack of supply; for example, see exhibit 20, which shows a clear negative relationship between price and median TOM over time.

Exhibit 19

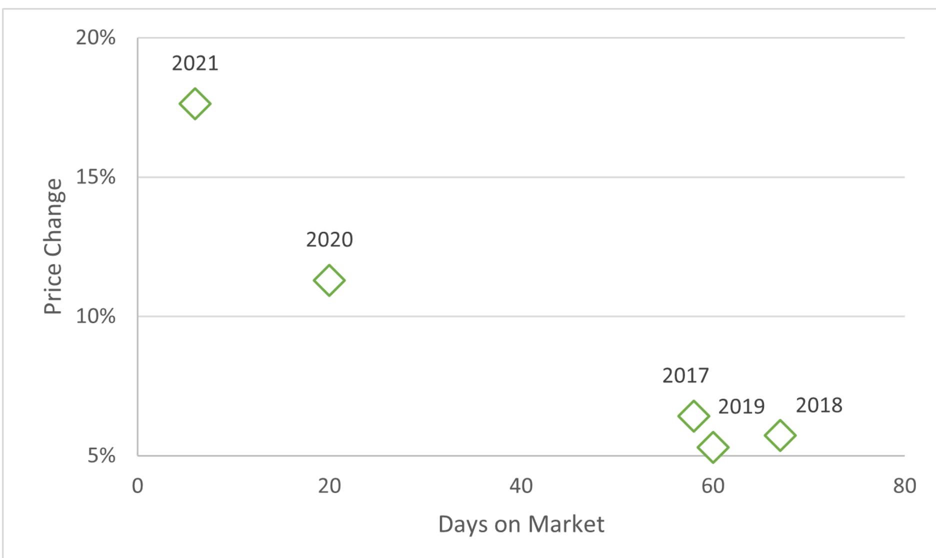
Supply, Liquidity, and House Prices



Note: Boxes represent the index and year-over-year price changes for the entire U.S. for only the month of November for the designated year.
Sources: Multiple Listings Service data provided by CoreLogic and the FHFA HPI® (purchase-only, not seasonally adjusted)

Exhibit 20

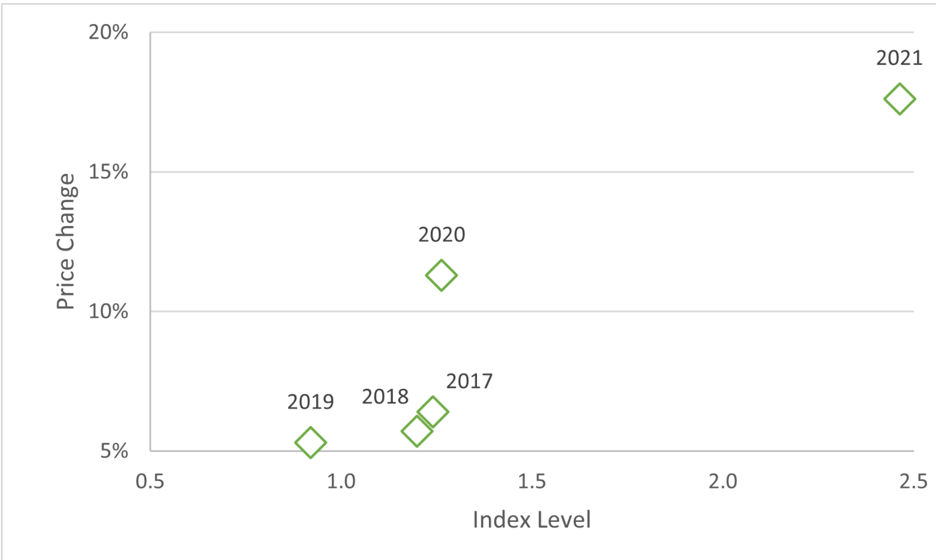
TOM and House Price Relationship Over Time



Note: Boxes represent the index and year-over-year price changes for the entire U.S. for only the month of November for the designated year.
Sources: Multiple Listings Service data provided by CoreLogic and the FHFA HPI® (purchase-only, not seasonally adjusted)

Exhibit 21

Supply, Liquidity, and House Prices



RPHI = repeat proportional hazard index.
Note: Boxes represent the index and year-over-year price changes for the entire U.S. for only the month of November for the designated year.
Sources: Multiple Listings Service data provided by CoreLogic and the FHFA HPI® (purchase-only, not seasonally adjusted)

For the few homes that were listed on the market, there were dramatic changes in their performance. Shortly after the pandemic there was a dramatic increase in the percent of homes that were withdrawn from the market, suggesting a reduction in the probability of sale. If a home did sell, however, its expected (median) time on the market also saw a reduction. One possible explanation is that due to the lack of supply, sellers were either holding out for higher prices or could not find a replacement property in which to move. Apart from the general uncertainty of the period, rapidly appreciating home prices and low interest rates during this period may have provided incentives for homeowners to stay put. Homeowners saw the values of their assets significantly grow and also may have been reluctant to give up a low interest rate on a recently refinanced mortgage, despite the cost of financing a home purchase being relatively low.

The more advanced measures tend to break later, though a precise break date cannot be identified due to the likely presence of multiple break dates. Graphically, after the initial jump, the advanced indices remained relatively flat until summer of 2022. Compared to pre-COVID levels, this jump corresponded to approximately double their previous trends. Both indices had a slight negative time trend prior to COVID-19, but now have positively sloped time trends. Qualitatively, the flattening of the indices in the summer of 2022 is not seen in the traditional measures. This, coupled with the delayed onset of changes to the RPHI and RMTI, suggests that censoring and unobserved heterogeneity are important to consider when measuring supply and liquidity of housing markets.

Using the traditional indices, evidence was provided that unobserved heterogeneity was the main driver of differences. For example, between March 2020 and December 2020, median TOM for sold and unsold both experienced decreases, although median TOM for sold properties was intuitively slightly smaller than that when including unsold homes. However, this effect of censoring is relatively small. Hence, one possible explanation for the divergence of traditional and advanced index levels is that between March 2020 and December 2020 there was a lot of unobserved heterogeneity that traditional indices ascribed to liquidity changes.

Conclusion

Housing supply and liquidity were greatly impacted by COVID-19, with the largest disruptions occurring at the start of the pandemic in March 2020. There were considerable differences between indices that controlled for censoring and unobserved heterogeneity, suggesting that traditional indices, which do not account for these issues, may confound changes in supply and liquidity with changes in sample composition and changes in the probability of sale. Importantly, the RPHI, RMTI, and percent withdrawn measures track changes in price appreciation very well.

This article has documented and described the changes in supply and housing market liquidity in the COVID-19 era. One issue worth exploring would be to examine any heterogeneity with respect to the increase in the proportion of withdrawn listings. For example, is there evidence of an increase in withdrawn listings across different geographies, or across different price tiers within a given geography? Future work could examine these effects and pin down a causal mechanism.

Future work could also focus on the determinants of these changes. One possibility would be to incorporate the possibility of multiple structural breaks to test for whether the different variants of COVID (Delta, Omicron) had effects on the market. Another avenue might be analyzing sample selection using hedonic characteristics, specifically looking at how the probability of sale and TOM vary across different types of homes. Additionally, more careful analysis of the distribution of TOM, for example decomposition techniques similar to that of Carrillo and Pope (2012), seems helpful for understanding what is driving the changes in liquidity. Finally, determining how changes in supply and liquidity vary across locations, such as distance to central business district (CBD), seems particularly useful if buyers are finding suburban homes relatively more desirable than urban homes.

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Are Settlement Patterns Changing in the United States as We Emerge from the COVID-19 Pandemic?

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Abstract

The COVID-19 pandemic dramatically changed the way people work, the state of the nation's housing markets, and, crucially, where people choose to live. This article identifies relocation patterns between counties of different population density types within metropolitan areas following the onset of the pandemic. Density types are defined as the population per square mile divided into four quantiles: high-density or urban (99th density percentile and above), intermediate-density (89th to 98th percentile), suburban-density (25th to 88th percentile), and rural-density (24th percentile and below). This analysis examines the county-weighted year-over-year change in the 12-month average of sales prices and sales volume as well as the year-over-year change in the four-quarter moving average of apartment rents and vacancy rates in 118 combined statistical areas that contain multiple counties of at least two density types. These combined statistical areas were classified into relocation patterns by first comparing the integral of price changes by density type both before and after the onset of the pandemic. This comparison was then supplemented with a visual identification of trends, using graphs to verify that the classifications made sense. The relocation trends are classified into four patterns: (1) Business as Usual, (2) the Donut Effect, (3) the Rise of Intermediate Cities, and (4) the City Paradox. The results showed that approximately 9 percent of the sales markets and 19 percent of the rental markets in metropolitan areas display a Business-as-Usual pattern, 30 percent of sales markets and 46 percent of rental markets in metropolitan areas exhibit the Rise of the Intermediate City trend, and 28 percent of sales markets and 20 percent of rental markets in metropolitan areas exhibit a Donut Effect trend. A subset of metropolitan areas classified as exhibiting a Donut Effect trend are likely to have been classified as exhibiting the City Paradox pattern, but this pattern was not examined in this analysis. Finally, case studies of each of the four resettlement patterns are presented.

Introduction

The COVID-19 pandemic vastly accelerated the adoption of telework in many industries and occupations as businesses and governments maintained operations while avoiding physical presence in worksites. During the first 2 months of the pandemic, approximately 35 percent of workers reported that they had switched from commuting to working from home (Brynjolfsson et al., 2020). Although many facets of life have returned to prepandemic norms more than 2 years later, the workplace for many of these office workers is likely forever changed. Even after the nation finally exits the pandemic, workers with jobs suitable for remote work will likely have options previously unavailable to them. These options include full-time remote work and hybrid work arrangements in which workers report to the office on a part-time schedule. In a comprehensive examination of the effects of vastly expanded remote work arrangements on social and economic policies in G-7 countries, the Organization for Economic Co-operation and Development (OECD, 2021) posits four potential directions for the evolution of settlement patterns in developed countries based on recent academic literature and their own analysis. OECD refers to the four scenarios as Business as Usual, the Rise of Intermediate Cities, the Donut Effect (Ramani and Bloom, 2021), and the City Paradox (Althoff et al., 2020). The scenarios are not mutually exclusive, particularly in a large and diverse country such as the United States. This article will describe each of the scenarios in detail and describe how an informed observer, rather than an econometrician, might observe their development in available data and then describe cases of places in the United States where they appear to be manifesting.

Settlement Pattern Scenarios

The *Business as Usual (with more telework)* scenario is characterized by employment centers remaining concentrated in big cities, and it is more likely to arise if employers resist allowing extensive full-time remote work. The need for some regular in-office time will maintain the attractiveness of central locations, but permanently higher telework levels will reduce peak traffic and transit ridership. No great redistribution of employment from current to new locations would occur, but within metropolitan areas, increased housing demand in outlying suburbs and immediate exurban locations is expected as longer commutes become somewhat more tolerable because they are somewhat rarer. Some movement of consumer services business to suburban and exurban locations may take place, following the population. Effects on house prices and rents would occur largely within metropolitan areas rather than between them as suburban and exurban prices and rents increase relative to those in more central locations. Building permits, often concentrated in outlying areas prepandemic, would continue as such, with perhaps somewhat greater intensity.

The *Rise of Intermediate Cities* scenario envisions more fundamental changes in employment locations among metropolitan areas as remote work technologies and practices remain widely adopted and more fully replicate the advantages of physical proximity in innovation and productivity growth. Initially, remote-enabled workers will gravitate toward intermediate cities, seeking lower housing costs and, perhaps, greater environmental amenities. As physical agglomeration effects weaken but do not disappear, firms will find advantages to relocating to smaller metropolitan areas with lower housing costs and other attractions for workers. The Rise of Intermediate Cities would be characterized by much more rapid house price and rent growth in smaller, as opposed to larger, metropolitan areas, as well as faster increases in building permit issuance in smaller areas. This trend is most prevalent between metropolitan areas, rather than within metropolitan areas, because many of the metropolitan areas that have experienced net in-migration from urban-density counties in this study contain only intermediate- and suburban-density counties.

The *Donut Effect* describes one of the more profound changes in the urban form of the four scenarios: a radical flattening of the density gradient from urban to outlying locations. It posits a weakening, but not complete breakdown, of physical proximity for the realization of agglomeration economies. High-skilled workers mostly move away from large city centers, seeking larger houses and more space, generally in the suburbs and urban periphery, but they remain connected to the city by the need to make occasional commutes. Eventually, due to reduced demand for centrality, city centers become more like surrounding suburbs, with lower-density housing and business use and more green space. If such a fundamental long-term transition were beginning, a very sharp change in the relationship of house prices and rents between central locations and outlying areas would be expected, with the outlying locations becoming relatively more valuable. The price shocks would be followed by adaptive reuse of existing structures and the demolition of more obsolete buildings for lower-density development. Permitting would remain strong in outlying areas, but these changes would be largely contained within metropolitan areas, without widespread movement among metropolitan areas of different sizes.

Like the Donut Effect, the *City Paradox* posits a weakening of the need for physical proximity to realize agglomeration effects, but it pushes further to assume that physical proximity agglomeration effects are nearly gone entirely. Thus, along with the flattening of the density gradient in major metropolitan areas, the City Paradox predicts a move toward smaller cities and rural areas as in the Rise of Intermediate Cities scenario. Consequently, along with a flattening of rent and house-price gradients in metropolitan areas of all sizes, the City Paradox would see moves from larger cities to smaller cities and rural areas, with the attendant move toward more equalized prices across metropolitan areas of different sizes.

The main thing to keep in mind at this point is that changes as comprehensive as the development of new settlement patterns will take generations to be fully realized because the United States typically only builds the equivalent of about 1 percent of the housing stock each year. That said, early signs of these changes can be seen in house prices, rents, and building permits.

Data and Analysis

To see if any of the settlement patterns within metropolitan areas have been taking hold and persisting since early 2020, the authors analyzed recent home sales and apartment data. For this analysis, all 3,100 plus counties in the United States were categorized as either urban, intermediate, suburban, or rural on the basis of their 2020 Census[1] resident population density. Counties in the

[1] The U.S. Census Bureau recognizes only urban and rural areas; therefore, the definitions of the terms in this report differ from theirs.

top 99th percentile of population density—such as New York County, New York; San Francisco County, California; and the District of Columbia[2]—were categorized as urban. Intermediate counties, categorized as counties with a population density between the 89th and 98th percentile, represent medium-sized metropolitan areas with thriving downtowns but to a lesser extent than urban counties. Counties such as Maricopa County, Arizona (Phoenix); Travis County, Texas (Austin); and Ada County, Idaho (Boise) are among the intermediate counties that were identified. Suburban counties are classified as those with population densities between the 25th and 88th percentile and include counties such as Sonoma County, California (Santa Rosa); El Paso County, Colorado (Colorado Springs); and San Bernardino County, California (Riverside-San Bernardino). The remaining counties, at the bottom 24th percentile of population density, were categorized as rural, and they include counties such as Gallatin County, Montana (Bozeman); Fairbanks North Star Borough, Alaska (Fairbanks); and Coconino County, Arizona (Flagstaff). County-level data were used to observe settlement patterns within the metropolitan area. For instance, to identify the Donut Effect, in which workers move just outside the central urban core, a comparison of urban, suburban, and intermediate counties within a metropolitan area—such as New York-Newark-Jersey City—is needed. This study may be the first to use this county population density categorization thresholds to analyze settlement patterns.[3]

Using the four population density categorizations—urban, intermediate, suburban, and rural—the authors examined 118 metropolitan areas with more than one county and at least one intermediate or urban county to identify within-metropolitan area trends. Two different periods of equal length were analyzed to determine the impact of the pandemic on settlement trends: April 2020 through October 2021, compared with September 2018 through March 2020. For the sales market, the authors used the year-over-year change of running 12-month county-weighted averages of sales prices, using CoreLogic sales data to calculate the cumulative difference in growth rates between each population density category. The cumulative difference in the prepandemic period was then compared with the cumulative difference in the period after the onset of the pandemic. The authors applied the same calculations for the apartment market, using year-over-year changes of a running four quarters of asking rents and stabilized vacancies using CoStar Group data. Important to note is that with this analysis, the authors are unable to classify a significant amount of settlement that is happening from one metropolitan area to another.

Sales and Rental Market Trends

Sales Market Trends

Both sales and rental housing markets have generally tightened across the country because of various factors, including low mortgage interest rates, greater rental affordability during the beginning of the pandemic, and, importantly, an increased ability to work remotely from anywhere. Compared with the prepandemic period of September 2018 to March 2020, average annual home sales price growth in most counties of the nation was higher in the post-pandemic-onset period,

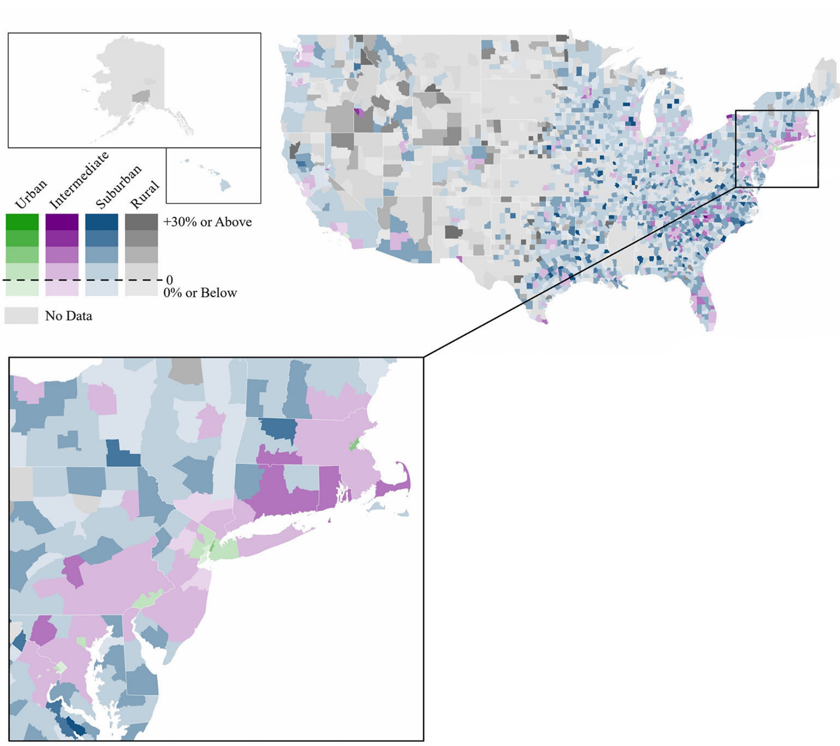
[2] The District of Columbia is treated as a county in this analysis.

[3] Meeker and Mota (2021) used a similar categorization in their report analyzing purchase mortgage applications, classifying high-density ZIP Codes as the top 20th percentile of people per square mile for each core-based statistical area, comparing them with lower-density ZIP Codes.

from April 2020 to October 2021, suggesting that the sales market tightened overall, despite relocations (CoreLogic, Inc., 2022). The impact of the pandemic on sales market conditions was most noticeable for urban counties, where average annual home sales price increases during the post-pandemic-onset period were higher in 96 percent of urban counties compared with prepandemic average annual growth. A still significant proportion of lower-density counties also recorded higher price growth during the post-pandemic-onset period, with average annual price growth higher in 86, 85, and 82 percent of suburban, intermediate, and rural counties, respectively (exhibits 1 and 2). The difference in the rate of price growth between the two periods was significant, with roughly three-quarters of intermediate, suburban, and rural counties reporting average annual price growth for home sales since April 2020 that was at least double the rate in the same county during the prepandemic period, and more than one-half of counties in the three lower-density categories reporting price growth at least triple the prepandemic rate. For urban counties, the difference was even starker, with 93 percent of urban counties reporting at least double the rate of price growth during the post-pandemic-onset period and 79 percent of urban counties reporting price growth at least triple the prepandemic rate.

Exhibit 1

Average Annual Price Growth for Homes Sold from September 2018 to March 2020, by County Density

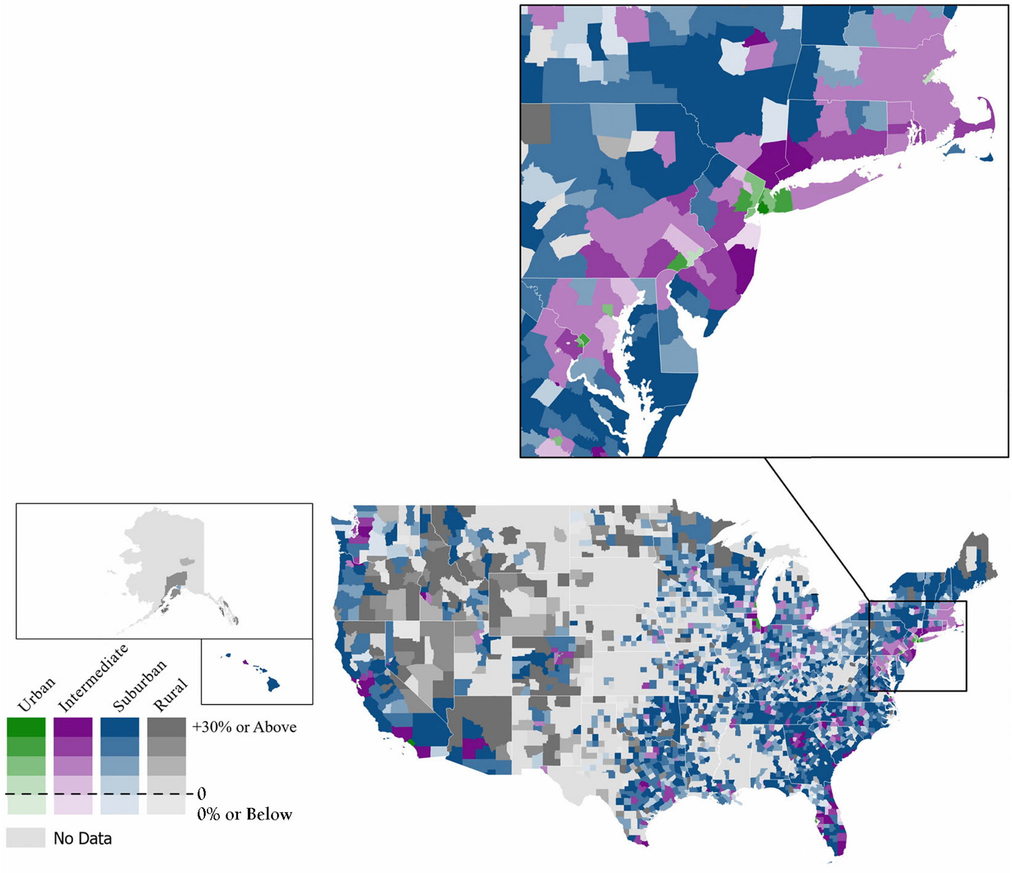


Notes: Because urban counties are classified as the top 99th percentile of population density, they account for only about 10 percent of counties in the United States and are, therefore, less visible on the national map. The area between the District of Columbia and Boston has a number of urban counties and has been highlighted for greater visibility.

Source: CoreLogic, Inc.

Exhibit 2

Average Annual Price Growth for Homes Sold from April 2020 to October 2021, by County Density



Notes: Because urban counties are classified as the top 99th percentile of population density, they account for only about 10 percent of counties in the United States and are therefore less visible on the national map. The area between the District of Columbia and Boston has a number of urban counties and has been highlighted for greater visibility.

Source: CoreLogic, Inc.

The sales data suggest that 19 metropolitan areas, or slightly more than 15 percent, fall into the Business-as-Usual settlement pattern, where the gap between sales and price growth of urban, intermediate, suburban, and rural counties within a metropolitan area is similar to the gap before the pandemic. About 38 metropolitan areas, or almost 32 percent of metropolitan areas, fall into the Donut Effect settlement pattern, with significantly higher growth in sales and prices in lower-density counties than higher-density counties and with a clear break between the prepandemic and post-onset-pandemic trends. A subset of these metropolitan areas is likely to fall into the City Paradox settlement pattern, but a lack of within-county price distribution prevented classification with the available data. Roughly 25 percent of metropolitan areas demonstrated a Rise of Intermediate Cities settlement pattern, with the highest growth in intermediate-sized counties. However, many metropolitan areas determined to be exhibiting this settlement pattern had only two density types: intermediate and suburban. In these metropolitan areas, sales and price growth in the intermediate counties was faster during the post-pandemic-onset period than in the suburban counties. Because only intra-metropolitan trends are examined in this report, it is also possible that demand from outside the metropolitan area to the intermediate counties is driving growth, rather than within-metropolitan area movement from the suburban to intermediate counties. Finally, 29 metropolitan areas did not exhibit clear characteristics of any of the four settlement patterns, and in three metropolitan areas, there was higher growth in high-density urban counties during the post-pandemic-onset period relative to lower-density counties, which was a reversal of prepandemic trends.

A plurality of counties in all density categories had growth in the number of home sales but to a much smaller extent than the differences in price growth would suggest, likely due to the historically low levels of housing construction after the Great Recession, supply and labor constraints on key inputs to residential development, and the natural inability of production to quickly meet demand. Around two-thirds of urban, suburban, and rural counties recorded an increase in average annual home sales during the post-pandemic-onset period, but the proportion was much lower, at 36 percent, in intermediate counties. For intermediate counties, this percentage still accounts for the plurality of counties because 39 percent of intermediate-sized counties have unreported data.

Apartment Market Trends

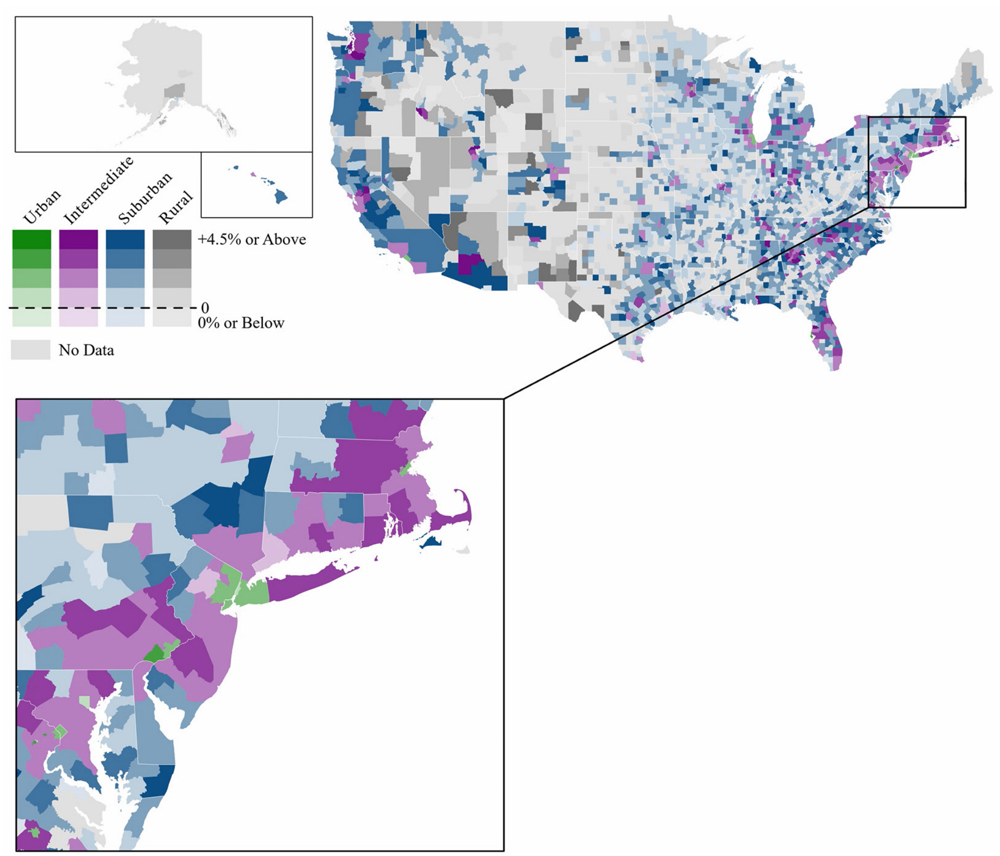
Unlike the sales market, in which home sales price growth during the post-pandemic-onset period was greater than before the pandemic almost uniformly across the board, apartment rent growth varied more on the basis of county density. An overwhelming 92 percent of intermediate-sized counties had higher average annual rent growth since the second quarter of 2020 than in the prepandemic period, suggesting that intermediate-sized counties across the country were the primary beneficiaries of pandemic-related rent growth (exhibits 3 and 4). In 86 percent of intermediate-sized counties, the stabilized vacancy rates have declined faster since the second quarter of 2020 compared with the prepandemic period (CoStar Group, 2022). Apartment markets in suburban counties were also significantly affected by pandemic demand; 60 percent of suburban counties had higher rent growth since the second quarter of 2020, whereas stabilized vacancy rates declined faster during the same period in 67 percent of suburban counties. The apartment market in urban counties responded similarly, with 61 percent of urban counties reporting higher rent growth and 55 percent reporting stabilized vacancy rates declining faster. Apartment markets in rural counties also tightened but to a significantly smaller extent, with only 44 percent of rural counties reporting higher rent growth since the second quarter of 2020.

The extent of rent growth during the post-pandemic-onset period was also significantly skewed toward intermediate-sized counties, with 80 percent of these counties recording average annual rent growth at one-and-one-half times higher than the rate of growth during the prepandemic period, and 62 percent of these counties recording double the rent growth. For urban, suburban, and rural-density counties, rent increases were one-and-one-half times higher than the rate of growth during the prepandemic period for a respective 35, 42, and 27 percent of these counties.

In the apartment market, 19 percent of metropolitan areas displayed the Business-as-Usual pattern. The pattern was unclear in 10 percent of metropolitan areas, and in 4 percent of metropolitan areas, greater growth occurred in higher-density counties, similar to the respective percentages for the sales markets. However, the apartment market in 46 percent of metropolitan areas demonstrated the Rise of Intermediate Cities pattern, and 20 percent of metropolitan areas demonstrated the Donut Effect pattern. Interestingly, in 51 metropolitan areas, or 43 percent, the categorization of the settlement pattern in the apartment market did not match the settlement pattern that the sales market suggested. Comparing the apartment market classification to the sales market classification revealed no clear trends.

Exhibit 3

Average Annual Rent Growth from 3Q2018 to 1Q2020, by County Density

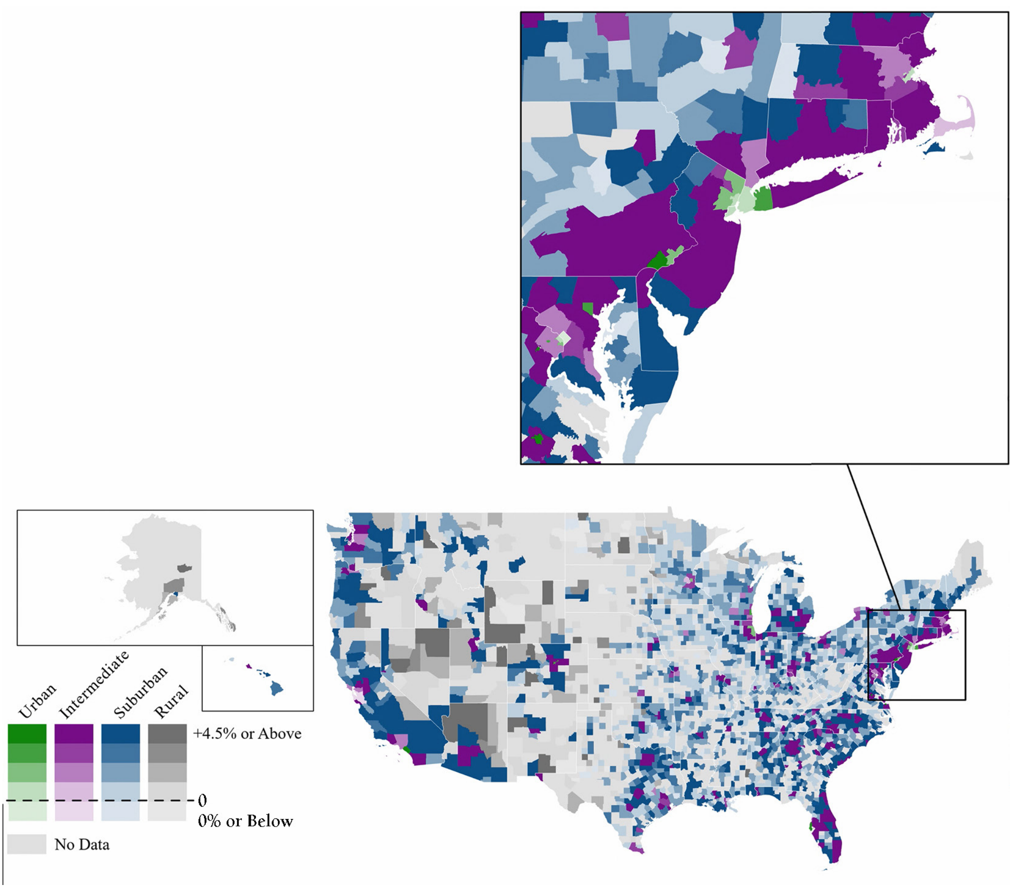


Notes: Because urban counties are classified as the top 99th percentile of population density, they account for only about 10 percent of counties in the United States and are, therefore, less visible on the national map. The area between the District of Columbia and Boston has a number of urban counties and has been highlighted for greater visibility.

Source: CoStar Group

Exhibit 4

Average Annual Rent Growth from 2Q2020 to 4Q2021, by County Density



Notes: Because urban counties are classified as the top 99th percentile of population density, they account for only about 10 percent of counties in the United States and are, therefore, less visible on the national map. The area between the District of Columbia and Boston has a number of urban counties and has been highlighted for greater visibility.

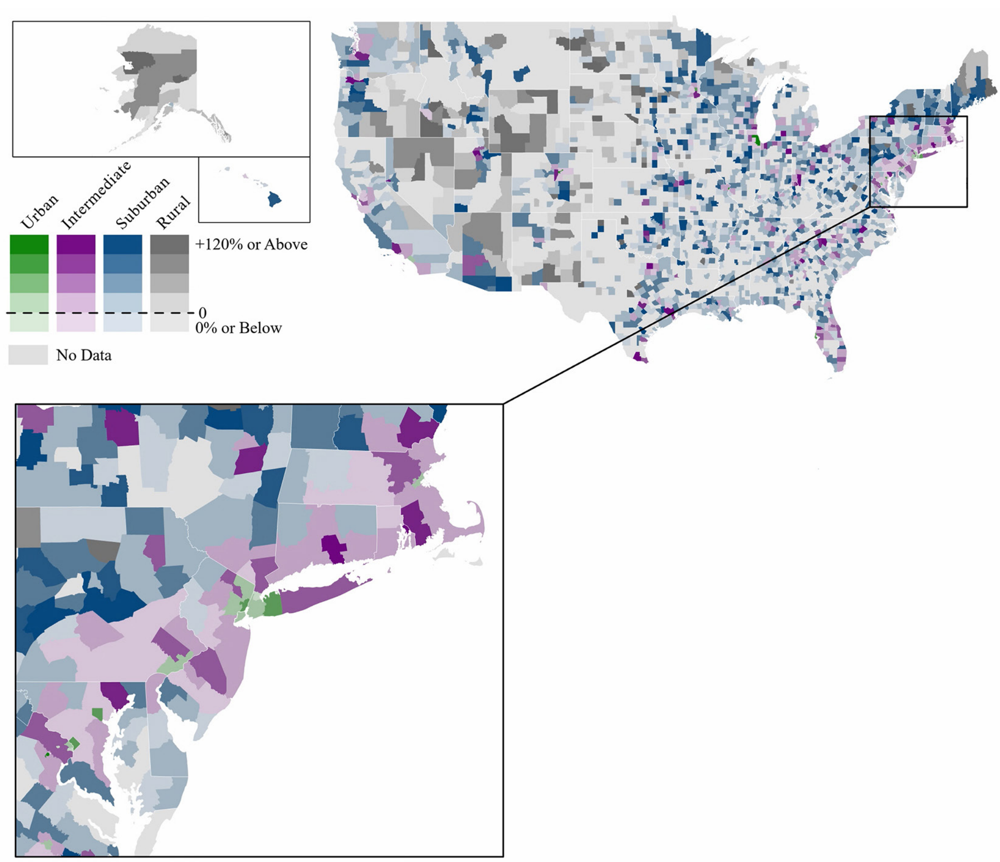
Source: CoStar Group

Residential Building Permit Trends

Residential construction activity, as measured by the number of building permits issued for multifamily units and single-family homes, typically should respond to tightening conditions in both the apartment and sales markets. During the prepandemic period, the number of residential units permitted increased in almost three-quarters of all counties, with positive growth in permits in 68 percent of urban counties, 72 percent of intermediate-sized counties, 72 percent of suburban counties, and 69 percent of rural counties (U.S. Department of Housing and Urban Development and U.S. Census Bureau, 2022). The response to sales market conditions was much swifter in lower-density counties, with single-family home permitting activity increasing in 76 percent of all counties, a proportion that was similar across all density types except for urban counties, where a higher 84 percent of those counties reported an increase in single-family building permits issued (exhibit 5). However, the reverse was true for multifamily construction activity, in which the number of multifamily units permitted increased in 16 percent of urban counties and 26 to 30 percent of lower-density counties during the period (exhibit 6).[4] For multifamily units, residential construction activity in almost one-half of the counties remained unchanged during the post-pandemic-onset period, likely a result of the push and pull of higher demand with greater supply and labor constraints on construction. Single-family construction activity, however, has been able to respond more quickly, and only a small fraction of counties of all density types—typically less than 10 percent—have not seen any change in the post-pandemic-onset period.

Exhibit 5

Average Annual Growth in Single-Family Homes Permitted from September 2018 to March 2020 Compared with April 2020 to October 2021, by County Density



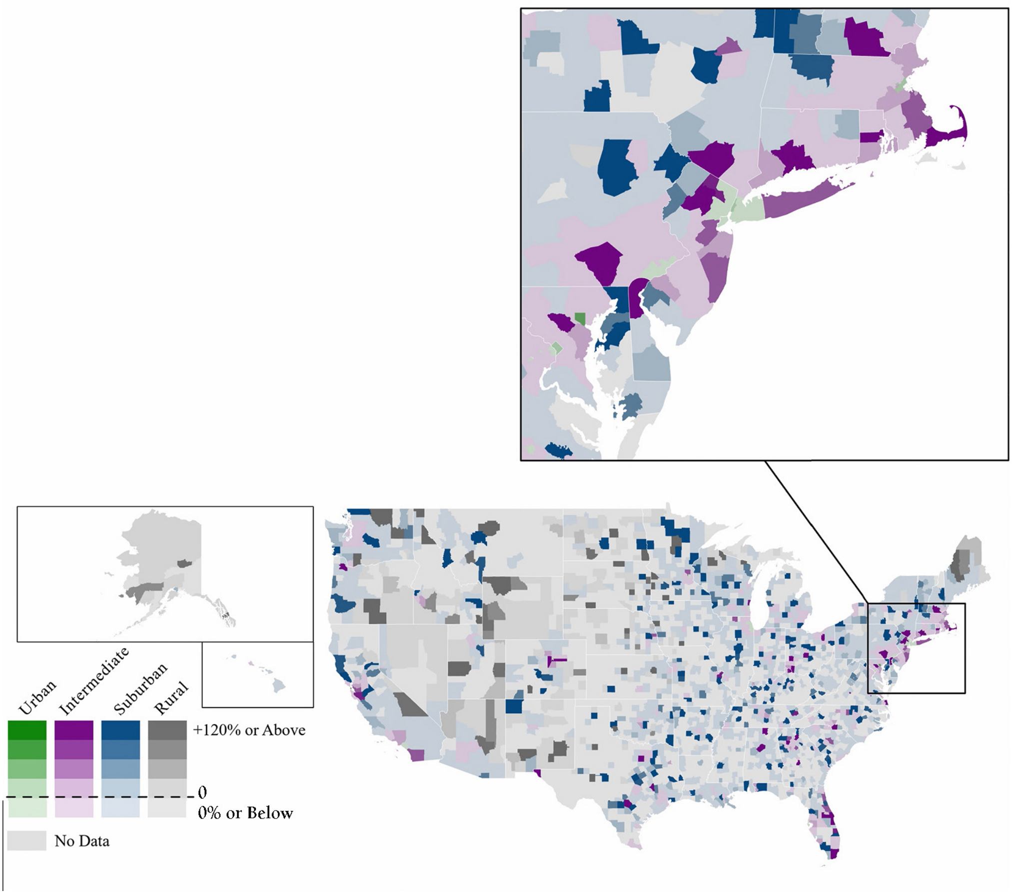
Notes: Because urban counties are classified as the top 99th percentile of population density, they account for only about 10 percent of counties in the United States and are therefore less visible on the national map. The area between the District of Columbia and Boston has a number of urban counties and has been highlighted for greater visibility.

Source: U.S. Department of Housing and Urban Development and U.S. Census Bureau, Building Permits Survey

[4] The Building Permits Survey collects data by structure type, not by the intended tenure of the unit. Therefore, permits for multifamily units include those for apartments, condominiums, and townhomes.

Exhibit 6

Average Annual Growth in Multifamily Homes Permitted from September 2018 to March 2020 Compared with April 2020 to October 2021, by County Density



Notes: Because urban counties are classified as the top 99th percentile of population density, they account for only about 10 percent of counties in the United States and are therefore less visible on the national map. The area between the District of Columbia and Boston has a number of urban counties and has been highlighted for greater visibility.

Source: U.S. Department of Housing and Urban Development and U.S. Census Bureau, Building Permits Survey

Settlement Pattern: Business as Usual (with more telework)

Case Study: Philadelphia-Camden-Wilmington, PA-NJ-DE-MD Metropolitan Area

The Philadelphia-Camden-Wilmington, PA-NJ-DE-MD metropolitan area is characterized as Business as Usual because growth rates in sales prices and apartment rents between counties of different density levels closely mirror one another, due in large part to the metropolitan area's high concentration of employment in the education and health services sector. Net out-migration from the Philadelphia-Camden-Wilmington metropolitan area from 2012 through 2017 helped drive down demand for homes. Average home sales prices in suburban and urban counties wavered between declining year-over-year and averaging low single-digit price growth until 2019. Following the onset of the pandemic, however, mortgage rates fell to historical lows, net in-migration increased, and, in late 2020, stock-holding households found their assets more valuable than they had been before the pandemic. These factors increased owner demand, and the metropolitan area saw home prices rise at unprecedented rates. Crucially, before the pandemic and after its onset, home sales and prices in the suburban counties grew at similar rates to the urban counties, separated by only a few percentage points. Despite the enactment of countermeasures to contain the pandemic and the adoption of remote work for white-collar jobs, a significant redistribution of the population to new locations does not appear to have occurred.

Many workers in the Philadelphia-Camden-Wilmington metropolitan area are employed in sectors that were either unable to transition to remote work or had strong intentions to return to full-time, in-person work. The largest payroll sector in the area, the education and health services sector, includes numerous jobs unsuitable for remote work. In the Philadelphia metropolitan area, this sector made up 21 percent of nonfarm payrolls in 2021 and supported more than 90 postsecondary educational institutions and nearly 60 hospitals (U.S. Bureau of Labor Statistics, 2022a). In the highest-density counties of Philadelphia and Delaware, the share of jobs in this sector was even more concentrated, at 34 and 25 percent of nonfarm payrolls in 2020 (U.S. Bureau of Labor Statistics, 2022b). The Philadelphia-Camden-Wilmington metropolitan area was not exempt from the widescale adoption of remote working at the onset of the pandemic; however, many workers with occupations in the professional and business services or financial activities sectors were able to relocate to more affordable housing in suburban counties, pushing suburban rents and home prices slightly higher than in urban areas.

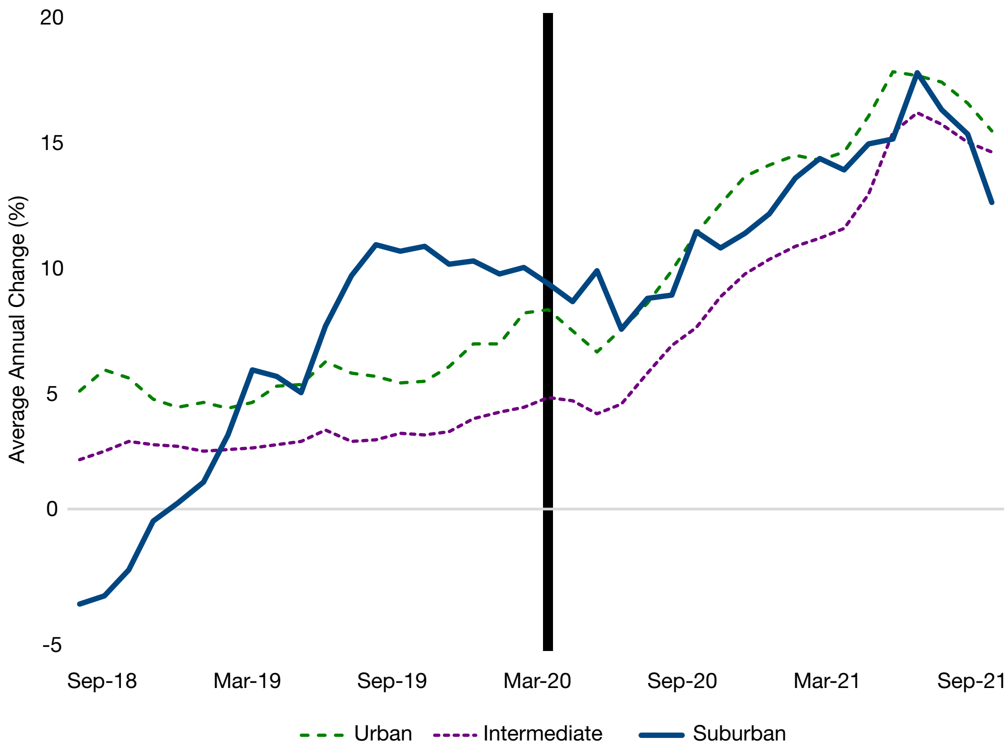
The relative importance of high-density urban counties as job centers in the metropolitan area remained strong, and increased housing demand pushed up apartment rents, apartment occupancy rates, home prices, and home sales at similar rates across counties of all densities.

The overlapping growth rates, as seen in exhibit 7, illuminate the nearly identical growth rates in home prices between density types both before and after the onset of the pandemic. Whereas price growth rose significantly for counties of all density types in the metropolitan area for much of the period after the onset of the pandemic, the difference in price growth among the density categories was similar to prepandemic trends, suggesting that the housing market tightened across the board. Sales price growth in densely populated urban counties and intermediate-sized counties was separated by an average of 3 to 4 percentage points after 2020, similar to the average of 2 to 3 percentage points before the pandemic (CoreLogic, Inc., 2022). Although variation in suburban price growth has increased since 2019, average price growth in suburban counties has generally been below that of urban counties.

Home sales volume similarly grew at accelerated rates for all counties, following a drop in home sales in response to stay-at-home orders instituted in the early months of the pandemic. Year-over-year growth in the running 12-month total of home sales reached 15 to 20 percent in July 2021 for counties of all densities—annual growth rates not seen in the metropolitan area since 2016. During the latter part of 2021, home sales growth was fastest in the highest-density counties of Philadelphia and Delaware.

Exhibit 7

Average Annual Price Growth for Homes Sold in the Philadelphia-Camden-Wilmington MSA, by County Density Illustrating "Business as Usual"

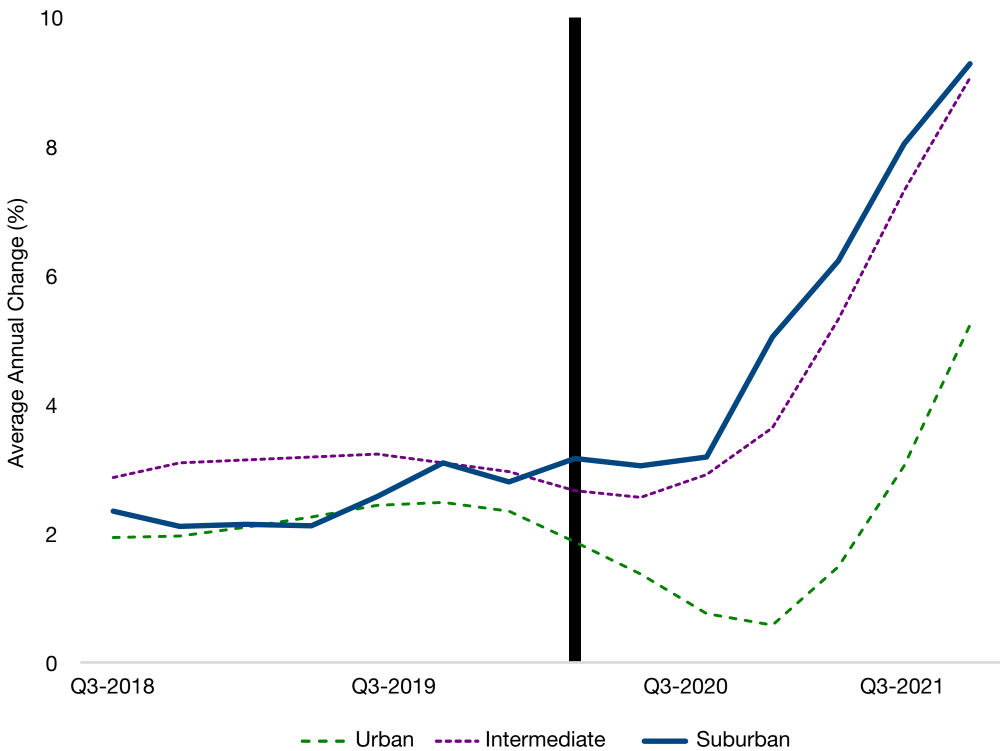


Source: CoreLogic, Inc.

The continued strength of the urban and intermediate areas of the Philadelphia-Camden-Wilmington metropolitan area is also evident in the apartment market. Average rents in all counties have historically grown at similar rates, and although rents in the highest-density counties have lagged those in lower-density counties, rents in intermediate-sized counties have grown at nearly the same rate as those in suburban counties following the onset of the pandemic, as can be seen in exhibit 8 (CoStar Group, 2022). Year-over-year growth in the running four-quarter average of rents has been nearly identical between suburban counties and intermediate-sized counties, separated by an average of 1 percentage point or less since the onset of the pandemic, similar to the gap in rent growth before the pandemic. Growth rates for rents in the highest-density counties have trailed rates in other, less dense counties, indicating relocation away from the downtown urban core. According to the Joint Center for Housing Studies of Harvard University (2020), renters are more likely to be single, have no children, and have more geographic flexibility than homeowners with similar telework flexibility, perhaps explaining why renter relocation is slightly more pronounced than owner relocation.

Exhibit 8

Average Annual Apartment Rent Growth in the Philadelphia-Camden-Wilmington MSA, by County Density Illustrating "Business as Usual," Although with Faster Suburban Rent Growth



Source: CoStar Group

Apartment vacancy rates have mirrored relocation trends in apartment rents and the sales market. Vacancy rates across area density types closely tracked one another before the pandemic, indicating a stable population distribution within the metropolitan area. Following the onset of the pandemic, vacancy rates across density types continued to track one another, but they decreased slightly faster in suburban and medium-density counties than in the highest-density counties of Philadelphia and Delaware. The discrepancy in vacancy rate change, as with rent growth rates, suggests that increases in rental demand affected all counties similarly but that some workers in the downtown urban core with the ability to adopt remote work relocated to less dense counties.

The Business-as-Usual pattern, or lack of relocation due to the relative strength of the downtown urban core to the surrounding suburbs, is likely to continue in coming years. One of Philadelphia's largest universities, Temple University, has expressed a commitment to returning to in-person instruction and established a Return Team to ensure a safe and complete return to on-campus activity.

The continued importance of the downtown urban core to the Philadelphia-Camden-Wilmington metropolitan area can also be observed in home construction activity, as measured by the number of single-family homes permitted. Total single-family homes permitted have increased annually since 2018, indicating that developers expect demand to continue through 2022. Specifically, from 2019 to 2021, the number of single-family homes permitted grew by an average of 30 percent in both urban and suburban counties (U.S. Department of Housing and Urban Development and U.S. Census Bureau, 2022).

The recent trend in the number of multifamily units permitted also indicates the expected strength of the urban core. Permits for multifamily units increased at an average annual rate of 30 percent in urban counties during 2019 and 2020 and more than five-fold during 2021 in urban counties, particularly Philadelphia County. However, the recent increase is not necessarily due to developers responding to a spike in apartment demand but rather a change in the tax abatement policy. In the suburban counties, no multifamily construction activity occurred from 2016 to 2020, but construction activity began to rise in 2021. The Indianapolis, IN and Columbus, GA metropolitan areas also present a Business-as-Usual settlement pattern.

Settlement Pattern: The Rise of Intermediate Cities

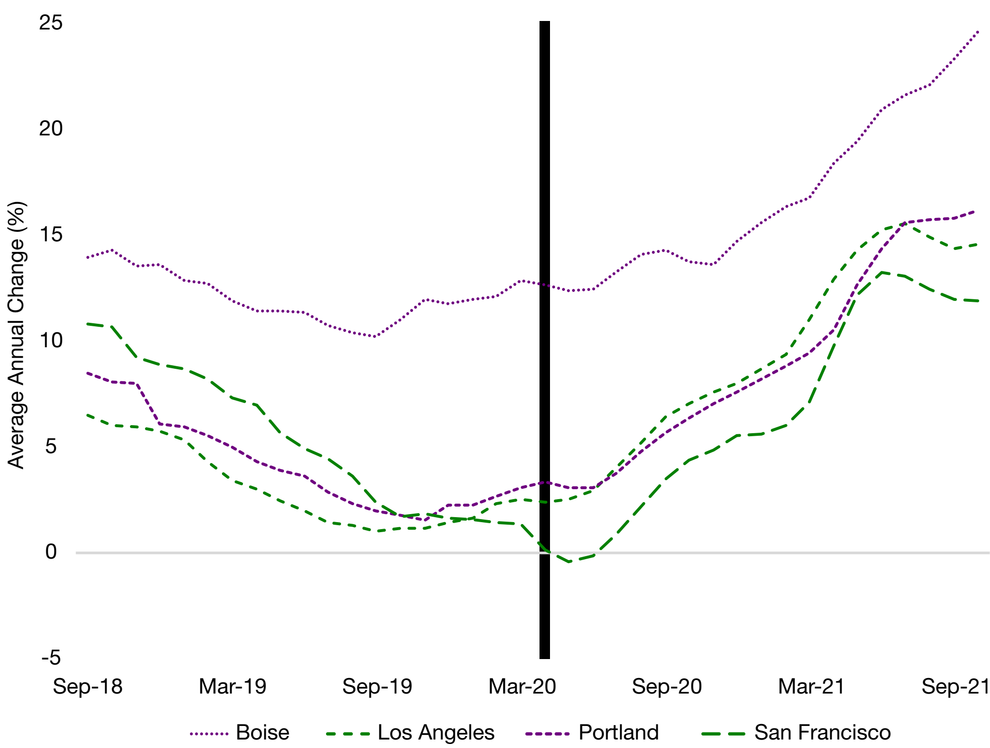
Case Study: Boise City, ID Metropolitan Area

The Boise metropolitan area fits the mold of a rising intermediate city, benefiting from the drain of residents from high-cost urban environments, and the pandemic has exacerbated this pattern. From 2015 to 2019, net in-migration to the Boise metropolitan area was strongest from higher-cost areas, with the largest concentration moving from the Los Angeles metropolitan area (U.S. Census Bureau, 2021a). Other popular areas of origin include the San Francisco and Portland metropolitan areas. This dynamic exists largely because of the relatively lower cost of living in the Boise metropolitan area coupled with many quality-of-life factors that entice people to the area, as evidenced by recent accolades. The Boise area ranked third on the list of Best Cities for Remote Workers 2021 (Chaplin et. al, 2021) and third on the list of Top U.S. Metros for Digital Nomads (Zillow and Yelp, 2021). Coworking spaces were available in the Boise metropolitan area before the pandemic, but several new operations have opened recently to support the increased use of remote work, including Nine to Five, Kiln, and Fort Builder, the latter of which opened two locations. Furthermore, apartment developers have recognized the shift in working patterns and are adopting new unit mixes to target the work-from-home demographic, with at least two proposed townhome developments that will include a large portion of live/work units. Live/work units are apartment homes that include a commercial component, such as an office or retail space, that is used by the primary occupant of the unit.

The influx of households from higher-cost and more urban metropolitan areas partly contributed to swift home sales price growth in the Boise metropolitan area, a pattern that has accelerated since the pandemic started. In 2015, the average sales price of a home in the Los Angeles metropolitan area was 3.0 times greater than the average sales price in the Boise metropolitan area, and that disparity fell to 2.5 times greater in 2019, before the pandemic (CoreLogic, Inc., 2022). Similar patterns are visible in the San Francisco and Portland metropolitan areas, where the disparities declined from 3.6 to 2.6 times and 1.4 to 1.1 times, respectively, during the same periods. Sales price growth in the Boise metropolitan area averaged almost 9 percent annually during the same period, compared with average annual growth of less than 5 percent in the Los Angeles metropolitan area and 6 and 7 percent in the San Francisco and Portland metropolitan areas, respectively (exhibit 9). During 2020, the average sales price of a home in the Boise metropolitan area rose 15 percent before accelerating to 24 percent in 2021 (CoreLogic, Inc., 2022). During the same time, in the Los Angeles metropolitan area, prices increased 8 and 15 percent, respectively, whereas price growth more than doubled in the San Francisco and Portland metropolitan areas compared with a year earlier, to 12 and 17 percent, respectively. These trends caused the disparity in housing costs to lessen further in 2021, and the average sales prices in the Los Angeles, San Francisco, and Portland metropolitan areas were 2.1, 2.6, and 1.1 times greater than in the Boise metropolitan area. The inflow of households from the urban, high-cost metropolitan areas, coupled with historically low mortgage interest rates, led to a surge in home sales in the Boise metropolitan area beginning in the fall of 2020, when the percent increase in year-over-year home sales reached double digits, a pattern that resurfaced in the spring of 2021. However, ongoing inventory shortages resulted in declining home sales in the Boise metropolitan area during the last part of 2021, and home sales were down 8 percent year over year. An increase in single-family home construction, with 8,350 single-family units permitted in 2021 compared with 8,150 units in 2020, could help ease some of the inventory crunch.

Exhibit 9

Average Annual Price Growth for Homes Sold in the Boise City MSA and Higher-Density MSAs Illustrating a "Rising Intermediate City"

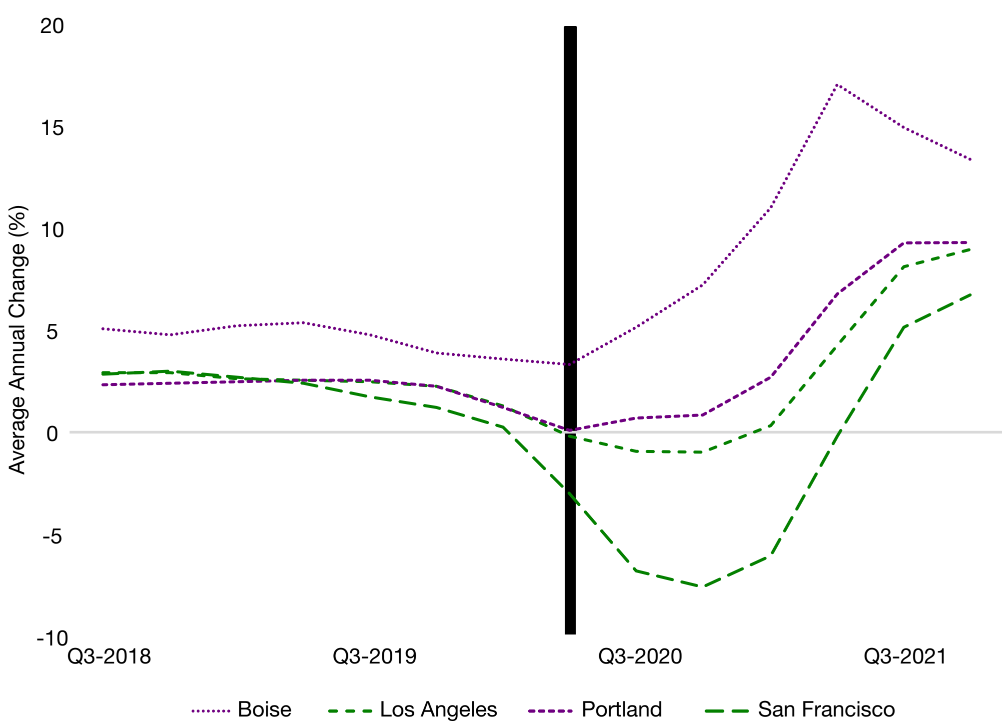


Source: CoreLogic, Inc.

Rental demand, especially for apartments, has increased in the Boise metropolitan area during the pandemic, partly because of a prolonged shortage of for-sale housing stemming from strong demand from higher-cost areas. In addition, some younger households have likely accumulated savings during the pandemic, whether by living with parents or roommates, receiving federal stimulus payments, or decreased spending on social events—or a combination of those factors—which in turn enabled new household formation; this subset of people is most likely to be renters. The apartment vacancy rate fluctuated little from 2015 through 2019, ranging from a high of 6.5 percent to a low of 4.3 percent. During the pandemic, the rate peaked at 5.9 percent during the third quarter of 2020 and has generally trended down since then (CoStar Group, 2022). Year-over-year rent growth ranged from 3 to 7 percent from 2015 through 2020, subsequently accelerating to double digits each quarter in 2021, coinciding with the gradual relaxing of COVID-19 restrictions (exhibit 10). Rent and vacancy trends were similar in the Los Angeles metropolitan area, although the magnitude of change was less than in the Boise metropolitan area, with accelerated rent growth starting in early 2021, whereas vacancy rates remained low. In the San Francisco metropolitan area, rents declined year over year from the second quarter of 2020 through the first quarter of 2021, whereas vacancy rates increased to their highest levels since at least 2012. Year-over-year rent

Exhibit 10

Average Annual Apartment Rent Growth in the Boise City MSA and Higher-Density MSAs Illustrating a “Rising Intermediate City”



Source: CoStar Group

growth returned during the third quarter of 2021, reaching 7 percent during the fourth quarter of 2021, which is the fastest rent growth since the fourth quarter of 2015. The apartment vacancy rate in the Portland metropolitan area was 5.1 percent or less from the onset of the pandemic through the fourth quarter of 2021, and like the other areas of comparison, rent growth increased significantly during 2021 but at lower rates than in the Boise metropolitan area.

To meet the rising demand for apartments, multifamily permitting in the Boise metropolitan area in 2021 reached its highest level since at least 1980, with more than 3,850 units permitted, surpassing the previous peak in 2019 by 26 percent. Multifamily permitting in 2020 decreased significantly from 2019 levels but was generally in line with average annual permitting of 1,575 units from 2014 through 2018. Although apartment markets in all three of these metropolitan areas have seemingly recovered from the effects of the pandemic, the data clearly show that the Boise metropolitan area has outperformed these more dense, urban markets, largely by continuing to attract high levels of residents from outside the metropolitan area. Other Rise of Intermediate City settlement patterns can be seen in the Phoenix, AZ and Charlotte, NC metropolitan areas.

Settlement Pattern: Donut Effect

Case Study: New York-Newark-Jersey City, NY-NJ-PA Metropolitan Area

In the spring of 2020, densely populated New York City was the epicenter of the COVID-19 pandemic in the United States, and as an early adopter of economic shutdowns and remote work to temper the spread of the virus, dramatic shifts occurred where people wanted to live within the larger metropolitan area.[5] Home sales fell precipitously at the start of the pandemic, and the average apartment vacancy rate rose to its highest level since the early 2010s throughout the entire metropolitan area. Shortly after this initial widespread softening of the housing market in the metropolitan area, the Donut Effect is visible in the home sales and rental data, with pronounced strength in markets of suburban and intermediate-density counties. During this time, home sales and prices in these counties grew at rates higher than during the housing boom,[6] and urban markets suffered a prolonged decline in home sales and prices. On the rental side, apartment rent growth in these counties has exceeded previous record rates, whereas rents declined in urban counties for the first time in at least a decade.

Beginning in August 2020, the running 12-month total of home sales in suburban counties of the New York metropolitan area continued to climb every month, reaching a peak of 43 percent year-over-year growth during the 12 months ending June 2021 (CoreLogic, Inc., 2022). Similarly, year-over-year home price growth in the suburban counties reached 44 percent by July 2021. For urban counties, home sales continued to decline through the 12 months ending April 2021. At its lowest point since the beginning of the pandemic, home sales in the urban counties declined 18 percent during the 12 months ending September 2020. Although urban county home prices did not decline, price growth in these counties has been consistently below suburban county price growth since late 2018, and the gap between urban and suburban county sales price growth

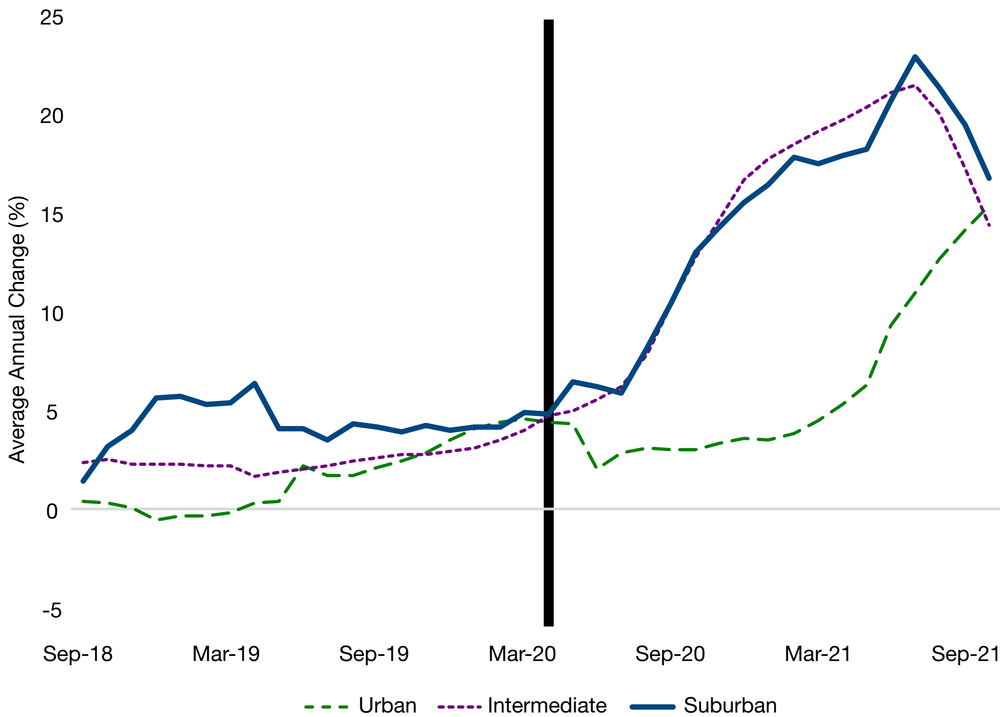
[5] As measured by sales and rental market data trends.

[6] The housing boom generally includes the 3 years before the start of the Great Recession in 2007.

has widened dramatically since the start of the pandemic (exhibit 11). The widest gap occurred during the 12 months ending February 2021, when home prices in suburban and intermediate counties increased 18 and 19 percent, respectively, but home prices in urban counties increased by less than 4 percent. These trends coincide with findings from the Office of the New York City Comptroller (2021), which analyzed United States Postal Service (USPS) change of address forms and found that the net loss from move-outs exceeding move-ins more than tripled from 2019 to 2020. A separate analysis of the same change of address data found that the majority of permanent movers—79 percent—did not leave the central metropolitan area; they moved to other urban boroughs but also to intermediate counties, such as Westchester and Suffolk Counties (Patino, Kessler, and Holder, 2021).

Exhibit 11

Average Annual Price Growth for Homes Sold in the New York-Newark-New Jersey MSA, by County Density, Illustrating the "Donut Effect"

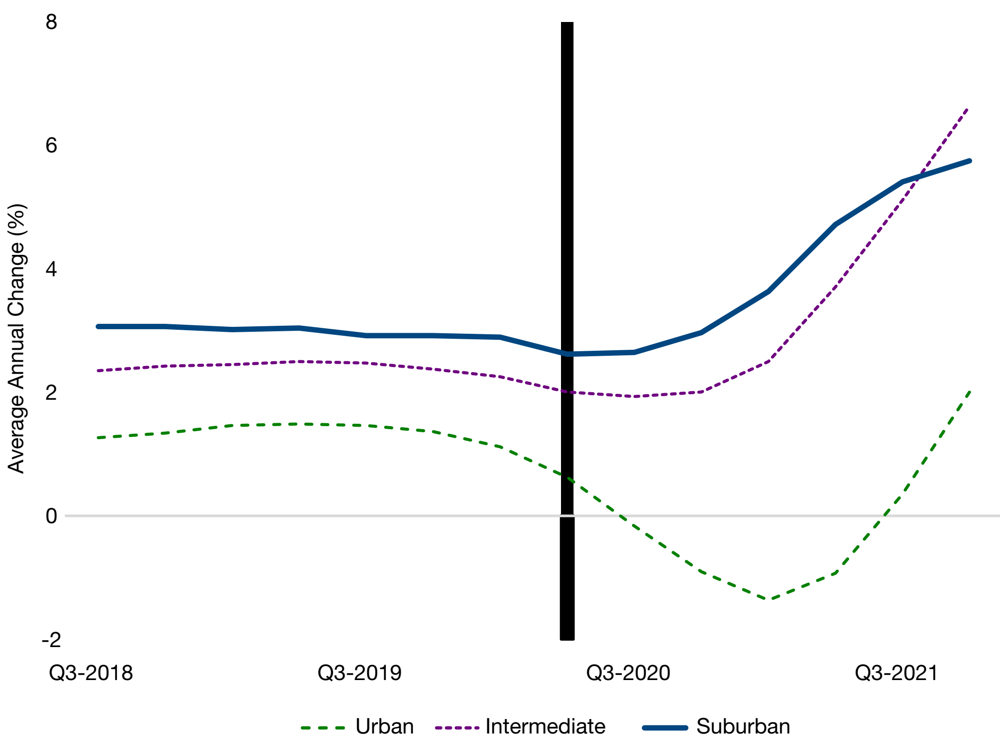


Source: CoreLogic, Inc.

The impact of the pandemic was similar in the apartment market, where urban counties continued to experience a year-over-year decline in average rents for three consecutive quarters, starting in the fourth quarter of 2020, whereas average rents in the suburban and intermediate counties increased faster than in previous years. From 2016 to 2020, rent growth in the suburban and intermediate counties of the New York metropolitan area consistently ranged from 2 to 3 percent (CoStar Group, 2022). After the first quarter of 2021, rent growth continued to climb, peaking at an average of 6 percent in suburban counties and 7 percent in intermediate counties. Although rent growth in the urban counties recently turned positive during the fourth quarter of 2021, it is still significantly below rent growth in the outlying counties of the metropolitan area, with a 2 percent year-over-year increase (exhibit 12). Even though rent growth is now positive, the pandemic's impact on rents has increased affordability, particularly in dense urban neighborhoods. According to a recent analysis, significant rent declines and high levels of inventory in New York City during the second half of 2020 more than doubled the number of homes—an addition of 40,000 units—that would be made affordable for HUD's Section 8 Housing Choice Voucher program, compared with the same period in 2019 (Wu, 2021). Large gains in the affordable inventory occurred in ZIP Codes covering the Bronx, and similar gains, on a percentage basis, were also recorded in ZIP Codes covering Manhattan, where the affordable inventory was extremely low before the pandemic.

Exhibit 12

Average Annual Apartment Rent Growth in the New York-Newark-New Jersey MSA, by County Density Illustrating the "Donut Effect"



Source: CoStar Group

This Donut Effect settlement pattern may not persist, however. The state of New York fully lifted all COVID-19 restrictions in June 2021, and public schools returned to full-time, in-person learning in September 2021. This full reopening overlaps with a sharp decline in the rate of both home sales and price growth in suburban and intermediate counties and a marked increase in both statistics for urban counties within the New York metropolitan area. During the 12 months ending November 2021, the average home sales price rose 40 percent in urban counties, 10 percent in suburban counties, and less than 1 percent in intermediate counties (CoreLogic, Inc., 2022). During the same period, home sales were up 30 percent in urban counties and down by 2 and 3 percent, respectively, in intermediate and suburban counties. The USPS change of address data analyzed by the Office of the New York City Comptroller (2021) similarly show an estimated net *gain* of approximately 6,325 movers into New York City from July to November 2021. The neighborhoods with the highest per capita net gains in movers were the same ones that had experienced the largest net losses during the early part of the pandemic: Chelsea/Midtown, Murray Hill/Grammercy, Battery Park City/Greenwich Village, and Chinatown/Lower East Side.

Residential building activity trends in the metropolitan area support the Donut Effect resettlement pattern; the share of permitting in the intermediate counties has increased since the pandemic, whereas the share of permitting in the urban counties fell. From 2015 through 2019, the urban counties captured 68 percent of all residential construction, and the intermediate counties accounted for 30 percent. The shift in household preferences because of the pandemic led to a 19-percent decline in construction activity in the urban counties in 2020, whereas the intermediate counties saw an 18-percent increase. Residential building increased in both categories in 2021, although growth was twice as fast in the intermediate counties, and permitting rose to its highest level since 2002. As a result, from 2019 through 2021, 42 percent of all residential building was in the intermediate counties, whereas the urban share fell to 55 percent. The suburban counties accounted for 2 percent or less of all residential construction since 2015.

The potential recent reversal of the Donut Effect pattern may reflect some movement from the suburban and intermediate counties back to the urban core, but it may also be due in larger part to new household formation in the newly reopened downtown, particularly among younger households. Households in New York City tend to follow a life cycle, and the pandemic and low financing costs may have pushed older millennial households or households on the edge to make the leap into the suburbs. The accumulation of household savings from federal stimulus money and COVID-19-related shutdowns and significant wealth generation from the bullish stock market may have encouraged this new household formation. The resurgence of entertainment and activities and the increasing affordability of residential housing in downtowns has increased the attractiveness of urban living for those new households. Established households, particularly larger ones with families and those in owner-occupied housing that have already moved to intermediate or suburban counties, are likely not accounting for a significant portion of movers into urban counties, especially if hybrid work is prevalent. That same reversal of the Donut Effect pattern has not occurred in the apartment market. The Donut Effect settlement pattern during the pandemic and its recent reversal can be seen in other large metropolitan areas, such as Boston, MA, and Denver, CO.

Settlement Pattern: City Paradox

Although the data from this study did not allow for identification of the City Paradox for all metropolitan areas, those areas that exhibited the Rise of Intermediate Cities scenario were supplemented with county-specific rental price data to examine trends by price point.

Case Study: San Francisco-Oakland-Berkeley, CA and Sacramento-Roseville-Folsom, CA

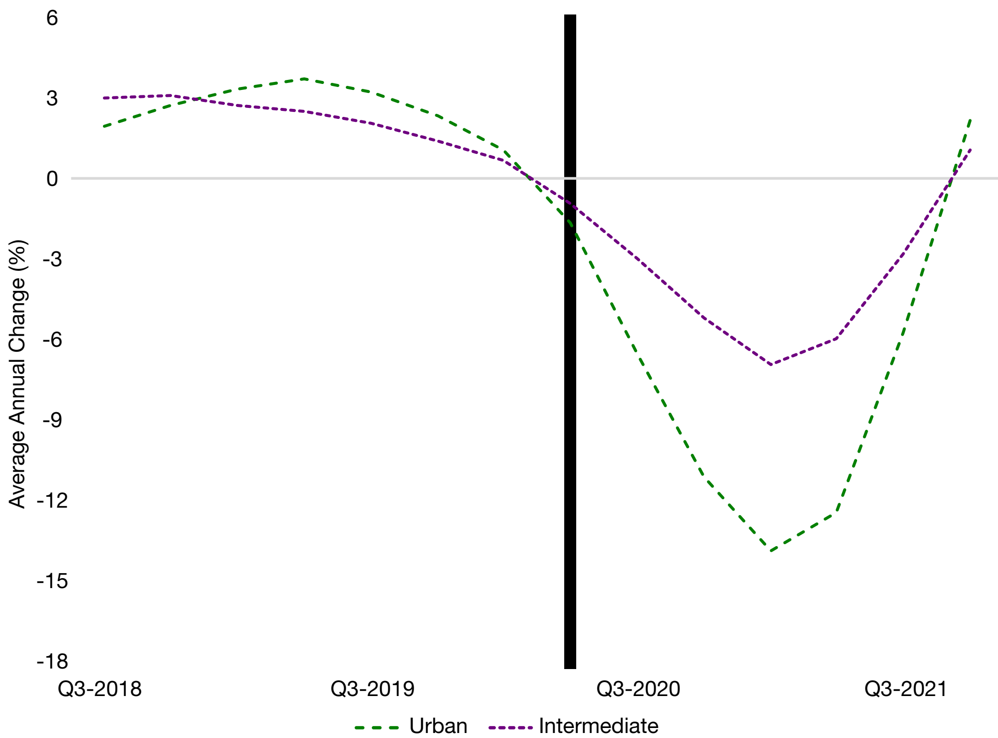
To examine the potential for the City Paradox settlement pattern, the authors analyzed not only trends between urban, intermediate, suburban, and rural counties within a metropolitan area but also the trends within different tiers of the housing market. Large and densely populated cities are the most expensive places to live, and, paradoxically, the cost is paid by workers with occupations most suitable for remote work. In these cities and metropolitan areas, highly skilled workers are likely to occupy rental units with the highest rents or homes in the highest price ranges. Although the home sales data used in this paper do not allow for the division of the market into different price intervals, the apartment market data can be analyzed at different classes. Class A apartments typically represent the highest-quality buildings and are generally newer properties with top amenities in well-located neighborhoods of the market. Units in these types of properties generally command the highest rents in a market. Class B and C properties tend to be older, may have some deferred maintenance issues or are in need of renovations, and are less likely to be professionally managed. The City Paradox settlement pattern would suggest that Class A units in the suburban and intermediate counties have faster rent growth and lower vacancies than Class A units in the urban and intermediate counties of a metropolitan area as highly skilled workers move outside the central business district.

Whereas many of the moves during the pandemic were likely temporary and within the same metropolitan area, analysis of the USPS change of address forms suggests that the story is different for moves out of the San Francisco metropolitan area. Permanent moves out of the metropolitan area increased by more than 23 percent, compared with an increase of 3 percent nationwide, mainly to other locations in California, such as Sacramento (Patino, Kessler, and Holder, 2021). Therefore, in examining the City Paradox pattern, the authors have evaluated trends in the San Francisco and Sacramento metropolitan areas to capture the moves of high-income earners to Sacramento. The only urban county in this larger area analyzed is the city and county of San Francisco, whereas all other counties in the Bay Area are categorized as intermediate density, and most counties in the Sacramento metropolitan area are categorized as suburban density except Sacramento County, which is intermediate density. El Dorado and Placer counties within the Sacramento metropolitan area include parts of Lake Tahoe, a popular second home and weekend retreat destination for many Bay Area households.

Class A year-over-year rent growth diverged widely at the start of the pandemic, with consecutive rent declines in urban San Francisco County from the second quarter of 2020 until the third quarter of 2021 (CoStar Group, 2022). The average rent decline in the county bottomed out at 14 percent during the first quarter of 2021. The intermediate-density counties of the San Francisco metropolitan area followed a similar pattern but to a much smaller extent, with rent declines bottoming out at 7 percent during the same quarter. Meanwhile, average Class A rent growth in the suburban counties of the Sacramento metropolitan area and intermediate-sized Sacramento County continued to increase every quarter until reaching peaks of 11 and 9 percent, respectively, during the fourth quarter of 2021 (exhibits 13 and 14).

Exhibit 13

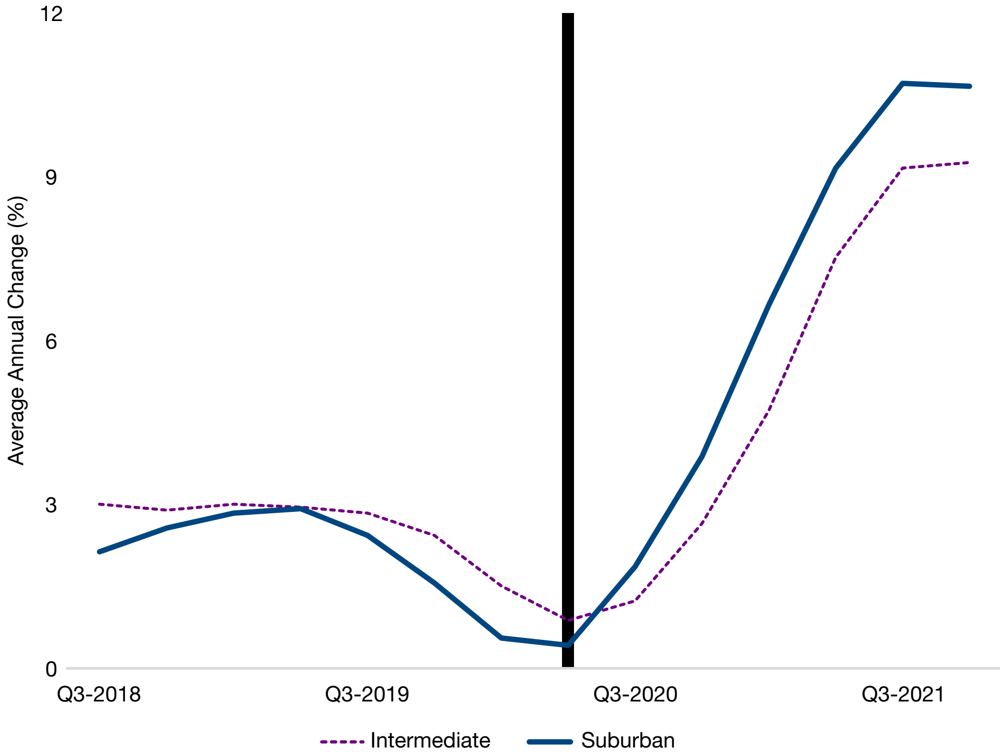
Average Annual Rent Growth for Class A Apartments in the San Francisco-Oakland-Berkeley MSA, by County Density



Source: CoStar Group

Exhibit 14

Average Annual Rent Growth for Class A Apartments in the Sacramento-Roseville-Folsom MSA, by County Density



Source: CoStar Group

These trends fit into the larger picture of movement out of the expensive and densely populated San Francisco County during the pandemic, particularly given the high proportion of people "untethered" to the region. The "untethered class" is a term coined by Apartment List, and it refers to people that fit several criteria: (1) they have an occupation that is easily transitioned into remote work, (2) they have no school-age children, (3) they rent their homes rather than own, and (4) either they have no spouse or their spouse has a remote-friendly occupation or is unemployed (Salviati, 2021). Younger, high-income earners generally meet these criteria. The San Francisco metropolitan area has the highest share of untethered workers in the country, at 13.5 percent, compared with 5.6 percent nationwide. Data on migration trends are not yet available for 2020 and beyond, but an analysis completed before the pandemic by the Terner Center at the University of California, Berkeley, and BuildZoom found that the highest-income households, earning more than $200,000 a year, generally migrated the furthest and left the state altogether at higher rates (Romem and Kneebone, 2018).

A comparison of multifamily building permit data before and during the pandemic shows that when workplace disruptions caused by COVID-19 were at their peak, multifamily building activity declined precipitously in the San Francisco metropolitan area and surged in the Sacramento metropolitan area. In 2020, the number of multifamily units permitted in the urban county of San Francisco and the intermediate-density counties in the San Francisco metropolitan area declined 38 and 32 percent, respectively, compared with 2019 (U.S. Department of Housing and Urban Development and U.S. Census Bureau, 2022). Whereas the decline in multifamily units permitted was similar in the urban and outlying counties of the San Francisco metropolitan area, permit activity in the two areas diverged in the subsequent recovery. In 2021, the number of multifamily units permitted increased 25 percent in the urban county of San Francisco but remained at the lowest level in 10 years (aside from 2020). This fact is in stark contrast to the intermediate-density counties in the San Francisco metropolitan area, where the number of multifamily units permitted in 2021 grew twice as fast as in the urban county and surpassed the 2019 level. Counter to the declines in permits of multifamily units in the San Francisco metropolitan area, the Sacramento metropolitan area in 2020 permitted multifamily units at levels not seen in more than a decade; the number of multifamily units permitted increased 58 and 109 percent in the intermediate-density county of Sacramento and the suburban counties, respectively. After the initial shock of the pandemic subsided, the number of multifamily units permitted in 2021 declined 22 and 30 percent in Sacramento County and its suburban counties, respectively, but remained notably higher than the average annual levels in the 5 years before the pandemic.

Conclusions

The COVID-19 pandemic sent shockwaves through the economy and housing markets in the United States. The rapid wide adoption of remote work in response to pandemic lockdowns may have jumpstarted a trend toward wider acceptance of remote work for the long term and changed the relationship between owner and renter housing demand and current settlement patterns. This study found early evidence of the development of all four post-COVID-19 settlement patterns identified by the OECD, although the evidence is not always consistent between owner and renter housing within markets. Furthermore, in some cases, the early trends toward these new settlement patterns are already slowing or even reversing.

Because it is early in the process, the question remains whether the changes observed so far will be permanent or if they represent an adjustment in the timing of regular generational housing demand cycles. Much will depend on the willingness of employers to permanently embrace higher levels of remote work or if further advances in communications technology (e.g., virtual reality telepresence) will be needed before they do. Observing changes in demand for housing and permanent changes in settlement patterns as the COVID-19 pandemic shockwave subsides will continue to be important for ensuring that housing development policies are adjusted appropriately.

Data Limitations and Future Research

Central to the analysis presented in this article is the classification of resettlement patterns by metropolitan area. Although most of the classifications can be easily identified using relative differences in rates of house price and rent change across locations, the authors acknowledge that the supplemental classification performed by visually observing graphed data is subjective.

In addition, the building permit data used in this article are by structure type and do not distinguish between units permitted for sale or rental purposes. At the national level, a substantial majority of multifamily units permitted are rental apartments, and nearly all single-family units permitted enter the home sales market; however, this pattern can vary significantly by metropolitan area.

As previously noted, the authors cannot classify a significant amount of settlement that is happening from one metropolitan area to another in this analysis, but it would be an interesting topic for future research.

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The Spatial Relationship Between the Low-Income Housing Tax Credit Program and Industrial Air Pollution

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Abstract

Housing is a key social determinant of health, but programs that create affordable housing may unintentionally concentrate residents in neighborhoods with unhealthy exposures, such as air pollution. This article examines whether neighborhoods with Low-Income Housing Tax Credit (LIHTC) properties have higher levels of industrial air pollution than comparable neighborhoods without LIHTC properties. The findings indicate that, within a given metropolitan area, more polluted neighborhoods are more likely to contain LIHTC properties (odds ratio [OR] 1.08 for 10-percentile-point increase in industrial air pollution). However, that relationship is no longer significant after accounting for neighborhood racial composition and socioeconomic status and is reversed when accounting for housing market characteristics (OR 0.95 for 10-percentile-point increase in industrial air pollution in fully adjusted model). These results provide the first estimates of the association between LIHTC properties and industrial air pollution at the national level and suggest that the disproportionate burden of air pollution exposure among LIHTC residents may be mediated by neighborhood conditions such as poverty and rental market quality.

Introduction

Living in safe and affordable housing is increasingly recognized as foundational for health and well-being (Taylor, 2018). Beyond the housing unit itself, neighborhoods can have a strong influence on long-term health outcomes by shaping access to economic and educational opportunities, as well as exposure to potential harms, such as crime or pollution (Diez Roux and Mair, 2010). Federal programs can provide residents with stable and affordable housing; however, those programs may unintentionally concentrate residents in neighborhoods with fewer resources or more harmful exposures. Thus, characterizing the neighborhoods in which these programs are built is important to fully understand their potential relationship to resident well-being.

The Low-Income Housing Tax Credit (LIHTC) is the nation's largest affordable housing program. Although previous studies of LIHTC have found that properties tend to be located in lower-income neighborhoods compared with renter households overall—and in predominantly minority neighborhoods and those with poorer schools (Ellen and Horn, 2018a; Horn and O'Regan, 2011; McClure and Johnson, 2015)—less is known about other features of LIHTC neighborhoods that may affect the health and well-being of their residents. Outdoor air pollution, specifically, has important health consequences, including increased prevalence of asthma exacerbations and incidence of heart disease, cancer, and stroke (Sun and Zhu, 2019). Few studies have examined the relationship between air pollution and the location of LIHTC properties.

The aim is to build on previous work by examining the association between industrial air pollution and the location of LIHTC properties. Industrial air pollution, rather than pollution from mobile sources such as cars or trucks, can be immediately linked to a physical location, such as a manufacturing plant. Although the distribution of pollution in the area around a point source is complex and not necessarily related to linear distance from the source (Chakraborty, Maantay, and Brender, 2011), policymakers and LIHTC developers may find that identifying point sources rather than mobile sources is easier for purposes of considering them in funding allocations. In addition, this study seeks to account for neighborhood-level characteristics, such as poverty level and racial or ethnic composition, that have been associated with the location of LIHTC properties.

Low-Income Housing Tax Credit

Administered through the Internal Revenue Service, LIHTC is the largest program designed to finance affordable housing in the United States. LIHTC awards tax credits to housing developers who build or renovate affordable housing, and it has produced more than 3 million units of affordable housing since its inception in 1986 (HUD, n.d.). Typically, these properties require that residents earn less than 50 to 60 percent of the Area Median Income. Some properties accept residents who exceed those income limits, although many residents fall well below them (O'Regan and Horn, 2013). Most properties are for general occupancy, but some have "target populations," such as families, senior residents, or formerly homeless individuals.

The location of LIHTC properties in each state is shaped by Qualified Allocation Plans (QAPs). QAPs are documents that provide guidance in how LIHTC funds should be allocated. States typically have more applications for funding than available funds, so, to prioritize applications, QAPs specify how points should be awarded for certain aspects of the development plan. Although some federal requirements are in place for QAPs, such as preferences for developing in high-poverty areas, states have considerable ability to customize and revise the QAPs to meet their own policy goals (Ellen and Horn, 2018b). For example, states may award more points to properties in low-income census tracts to promote revitalization. Alternatively, states may incentivize development in "high-opportunity" areas, such as high-income neighborhoods or areas near schools, jobs, or public transportation. LIHTC funding can also be used to revitalize existing housing and can be combined with other funding streams, such as the HOPE IV, Rental Assistance Demonstration (RAD), or Choice Neighborhoods. States recertify QAPs regularly, so priorities may change over time on the basis of the needs and interests of the state housing agency and other stakeholders. Recent initiatives across several states have attempted to prioritize LIHTC development in areas that may offer more opportunities for low-income residents (Ellen and Horn, 2018b). Various mechanisms within QAPs that incentivize developments in high-opportunity areas can effectively decrease new LIHTC development in low-income and predominantly minority neighborhoods (Ellen and Horn, 2018b).

Many states have used QAPs as mechanisms to promote the health of LIHTC residents, including environmental building standards that promote energy efficiency, avoidance of toxic materials, and lead abatement (Shi, Baum, and Pollack, 2020). QAPs may also incentivize proposals with co-located services, such as health screenings, nutrition counseling, or case management (Shi, Baum, and Pollack, 2020). Finally, QAPs may award additional points for proposals located near health-promoting services, such as community health centers, grocery stores, or parks (Shi, Baum, and Pollack, 2020). Developers recognize the inherent challenges and tradeoffs in these approaches, however; for example, building a property farther from a busy highway may decrease traffic emission exposure but also decrease the visibility of advertising about the property (Shi, Baum, and Pollack, 2020). Overall, more research is needed on how LIHTC developments can promote health beyond housing affordability alone; those data could come in the form of Health Impact Assessments to characterize the health benefits of LIHTC across sectors (Shi, Samuels, and Pollack, 2017).

Extensive literature has characterized the demographics of neighborhoods where LIHTC properties are located. LIHTC properties tend to be built in areas with higher poverty rates and greater unemployment, compared with renter households nationwide (McClure and Johnson, 2015). LIHTC properties are also constructed in areas with a higher proportion of Black residents (Horn and O'Regan, 2011). Although most units are in metropolitan areas and central cities, LIHTC properties are also increasingly being built in suburban areas (McClure, 2006).

LIHTC properties tend to be in areas with fewer resources than areas where rental properties are located overall. LIHTC households are more likely to live in neighborhoods with poor labor market engagement and worse school quality (Ellen, Horn, and Kuai, 2018). LIHTC neighborhoods, compared with other, similar neighborhoods, have poorer sidewalk completeness, which is a measure of walkability (Woo, Yu, and Lee, 2019). Compared with rental housing overall, LIHTC properties experience better transit access and affordability (Ellen, Horn, and Kuai, 2018); however, less is known about other aspects of neighborhood quality, especially those that may have an impact on health.

Air Pollution

One important feature of neighborhood quality is air pollution. Air pollution includes many different types of chemicals, often classified into criteria air pollutants and hazardous air pollutants. Criteria air pollutants—including PM2.5 (particulate matter with diameter < 2.5 microns), lead, carbon monoxide, and ozone—are present in larger quantities in the environment and are closely regulated by national emissions standards (EPA, 2021a). Hazardous air pollutants include hundreds of chemicals that have more serious health effects per "dose" but are present in smaller quantities overall (EPA, 2021b).

Air pollution has an important role in disease nationally. Outdoor air pollution has been linked with a host of adverse health outcomes, including asthma, chronic obstructive pulmonary disease (COPD), cancer, stroke, and heart disease (Adamkiewicz, Liddie, and Gaffin, 2020; Kampa and Castanas, 2008; Schraufnagel et al., 2019). In particular, PM2.5 has been widely studied as a key correlate of adverse health outcomes, including heart disease, stroke, and respiratory illness, and is a significant contributor to mortality worldwide (Bu et al., 2021; Rajagopalan, Al-Kindi, and Brook, 2018). Other types of air pollution beyond PM2.5 are also known to damage health. Exposure to hazardous air pollutants has been associated with a wide variety of acute and chronic health effects, including asthma, cancer, neurological disease, and cardiovascular dysfunction (Cicalese et al., 2017; Hill et al., 2021; Malek et al., 2015; Moore and Hotchkiss, 2016). Hazardous air pollutants have also been linked to children's educational outcomes, including reduced executive function, poorer early cognitive ability, and lower standardized test scores (Gatzke-Kopp et al., 2021; Grineski, Collins, and Adkins, 2020; Lett, Stingone, and Claudio, 2017). These effects on health and well-being persist even after controlling for race and socioeconomic status, suggesting that air pollution is independently associated with adverse outcomes rather than simply a correlate of neighborhood disadvantage.

Both criteria and hazardous air pollutants are generated from multiple sources. Industrial sites, such as factories, refineries, and power plants, produce a large component of outdoor air pollution, especially hazardous air pollutants. Other sources of air pollution include mobile sources, such as cars and trucks, and natural sources, such as forest fires (EPA, 2021d).

Recent studies suggest that industrial air pollution causes adverse health outcomes independent of other pollution sources and should be examined on its own (Persico, Figlio, and Roth, 2016; Persico and Venator, 2021). Much of this research has focused on proximity to Toxics Release Inventory (TRI) facilities. TRI sites are industrial pollution sites which release chemicals known to cause adverse health or environmental impact and have been mandated to report annual emissions data to the U.S. Environmental Protection Agency (EPA; 2021f). Geographic proximity to a TRI facility during gestation correlates with a higher rate of children dropping out of high school and with lower family income over a lifetime (Persico, Figlio, and Roth, 2016). In schools closer to TRI sites, children perform significantly worse on math and reading tests than the general population, even when accounting for race, gender, and socioeconomic status (Persico and Venator, 2021). Cognitive disabilities are also more common among populations who were closer to TRI sites during gestation (Persico, Figlio, and Roth, 2016).

Industrial air pollution, compared with that from other sources, is particularly salient to the residents of neighborhoods near these sites. Residents who live near an industrial site report a higher perception of pollution risk compared with those who live near sources of vehicular pollution (Chakraborty et al., 2017). Much environmental activism has centered around closure or decontamination of industrial sites (Allen et al., 2019; Bratspies, 2020; Knezevich and Condon, 2020). In addition, neighborhoods with TRI sites can become "corrosive communities" with decreased civic engagement and low public trust in government (Brown, 2022; Freudenburg and Jones, 1991).

Air pollution exposure—whether from industrial or other sources—disproportionately affects low-income communities and communities of color (Jones et al., 2014). Historically, Black homebuyers and renters were limited to lower quality neighborhoods by discriminatory policies, such as redlining and exclusionary zoning (Pietila, 2010). As a result of those discriminatory policies, Black Americans are more likely to live in more polluted cities overall and in more polluted neighborhoods within cities (Ash and Fetter, 2004). Areas that received the worst redlining "grade" currently experience a significantly higher burden of air pollution, as well as other environmental hazards, including extreme heat and toxic waste sites (Lane et al., 2022). Present-day residential racial segregation is linked to disparities in both criteria and hazardous air pollutants, which may contribute to well-described disparities in morbidity and mortality (Morello-Frosch and Lopez, 2006).

These disparities are particularly apparent in the distribution of industrial air pollution. Facilities that produce air pollution and other environmental hazards are more likely to have been built in low-income and majority-minority areas (Zwickl, Ash, and Boyce, 2014). Industrial air pollution also tends to be higher in cities with greater residential racial segregation (Ard, 2016). Although industrial air pollution has declined nationwide over the last several decades, racial inequities in pollution exposure persist (Salazar et al., 2019). Even in states with stronger environmental protection policies, the disproportionate burden of industrial air pollution on residents of color has not significantly decreased over the past several decades (Bullock, Ard, and Saalman, 2018).

Air Pollution and Public Housing

Limited literature exists to describe the burden of air pollution among recipients of housing assistance programs. Most studies focus on indoor air pollution, especially that from secondhand smoke, given recent legislation banning smoking in public housing developments (Anastasiou et al., 2020; Galiatsatos et al., 2020). Relatively few studies examine outdoor air pollution exposure among federally assisted households, however. Recent attention has focused on the proximity of public housing developments to Superfund sites or hazardous waste sites in need of remediation. Reports from EPA and the U.S. Department of Housing and Urban Development (HUD) estimate that approximately 77,000 federally assisted households are living within 1 mile of the most polluted Superfund sites (Coffey et al., 2020). These figures provide a conservative estimate of the burden of environmental contamination on federally assisted households, as this number does not include all hazardous waste sites or other housing programs. Extensive organizing by community members and advocacy organizations has shone a spotlight on the health hazards of living near these toxic waste sites, as well as poor coordination between federal, state, and local agencies responsible for housing, pollution, and health (Coffey et al., 2020).

Other analyses examine the location of public housing in relationship to major roadways. In New York State, a significant proportion of public housing developments are in close proximity to major roadways, which may confer greater risk for morbidity and mortality due, in part, to air pollution from mobile sources (Krisko, 2021). Almost 2 percent of public housing developments in the state are in census tracts where PM2.5-related mortality is twice the state average (Krisko, 2021).

Previous Work on LIHTC and Air Pollution

Air pollution is an important but understudied aspect of the neighborhood environment where LIHTC properties are located. One key study describing air pollution exposure among LIHTC properties is that of Ellen, Horn, and Kuai (2018). In that study, Ellen and colleagues used a sample of 12 states for which they were able to obtain individual-level data on LIHTC households. The study included all LIHTC units built up until 2011 or 2012, depending on the quality of state-level data. The sample was constructed with each observation representing either an LIHTC unit or a rental unit. Then, the authors used multiple measures of neighborhood opportunity from the HUD Affirmatively Furthering Fair Housing dataset, including the HUD environmental health index, as dependent variables to describe differences in the neighborhood conditions of LIHTC units compared with other rental units. The authors found that LIHTC units were in neighborhoods with higher poverty rates, worse schools, and lower labor engagement. LIHTC units were also found in neighborhoods with poorer environmental quality, although the magnitude of this difference (1 percentile point) was lower than the difference in other percentile-based indices. By contrast, LIHTC units were found in neighborhoods with a greater percentage of tenants using public transportation and more affordable transportation for low-income residents. Using tenant-level data, the authors also found that, compared with non-poor LIHTC tenants, low-income LIHTC households lived in neighborhoods with greater air pollution. Similarly, Black and Hispanic LIHTC households lived in neighborhoods with greater air pollution than White LIHTC households, even after controlling for household poverty status. Notably, their regressions included fixed effects for the metropolitan statistical area (MSA) but no other neighborhood-level covariates. Thus, the primary findings represent average differences within an MSA and do not account for possible confounders, such as neighborhood poverty level, racial segregation, or other factors that may influence LIHTC siting decisions and the burden of air pollution.

In another analysis focusing on traffic exposure, transit access, and walkability, LIHTC properties were compared with housing choice voucher units in Orange County, California (Houston, Basolo, and Yang, 2013). Compared with voucher units, LIHTC properties were more likely to be found in neighborhoods with commercial, transportation, utilities, or vacant land use and less likely to be found in residential areas. When adjusted for block group demographics and land use, LIHTC properties were less likely than voucher units to be found in high-traffic areas and were thus less exposed to vehicular air pollution. That relationship was not significant when adjusting for walkability and transit characteristics of the neighborhood, however. Similar to trends described above in the characteristics of LIHTC neighborhoods, the findings from Ellen, Horn, and Kuai

(2018) and Houston, Basolo, and Yang (2013) suggest that LIHTC units may experience more air pollution than rental units overall but less than voucher units.

Present Study

This study compares industrial air pollution exposure in neighborhoods with LIHTC properties with neighborhoods without LIHTC properties, although how neighborhood conditions may be contributing to this relationship is unclear. Given racial and economic disparities in both the location of LIHTC properties and the distribution of industrial air pollution, it is hypothesized that neighborhoods with LIHTC properties will be exposed to a higher level of industrial air pollution than neighborhoods without LIHTC. Finally, it is hypothesized that these disparities will persist even after controlling for neighborhood characteristics.

Methods

LIHTC

A publicly available database of LIHTC properties built from 1986 to 2018 was obtained from HUD. Available data include property address, coordinates, and census tract, as well as number of rental units. Properties that were listed as “no longer monitored” by the LIHTC program (~15 percent) were retained because they may still be low-income properties (Ellen, Horn, and Kuai, 2018).

The initial dataset was restricted to 48,278 properties in the 50 states and Washington, D.C. Properties that could be successfully geocoded were retained (n=46,296). Entries corresponding to multiple buildings within the same property were merged into one observation, and duplicate entries were removed, leaving 43,044 properties. Properties were dropped if they were put into service after 2018 or contained 0 or missing units (n=314). For properties with missing year put into service (n=3,306), the value was replaced with the year that funds were allocated plus 1 year, representing the average difference between the year put in service and the year funds were allocated among properties that had both values. Properties missing both the year put in service and the year of funding allocation were dropped (n=1,733). Properties were categorized by year put into service into three time periods: early years (1987–1999), housing bubble era (2000–2007), and crash and recovery period (2008–2018), following the approach of McClure and Schwartz (2021).

Census tracts were designated as having no LIHTC units or least one LIHTC unit. Tracts that could not contain LIHTC properties were removed, including tracts that completely cover bodies of water (n=317); other nonhabitable areas, such as airports (n=423); and tracts with no inhabitants (n=47). Tracts were also removed if they did not contain any multifamily units, defined as a building containing two or more housing units, based on the 2014–2018 American Community Survey 5-year estimates (n=4,709, or 6.5 percent of all remaining tracts). Finally, following the approach of Ellen, Horn, and Kuai (2018), the dataset was restricted to those tracts with greater than 200 inhabitants located in metropolitan areas, as defined by the U.S. Census Bureau 2018 metropolitan divisions (U.S. Census Bureau, 2021).

The final dataset includes 56,379 tracts overall and 16,406 tracts containing LIHTC properties. These metropolitan LIHTC tracts include 32,332 properties and 2.6 million units, or ~67 percent of the entire LIHTC stock.

Industrial Air Pollution

Industrial air pollution was described using the 2018 Risk-Screening Environmental Indicators (RSEI) data (EPA, 2021e). RSEI compiles information reported annually to the Environmental Protection Agency on the release of more than 700 toxic substances, including all hazardous air pollutants, from Toxics Release Inventory (TRI) sites (EPA, 2021f). The RSEI score incorporates dispersion variables such as height of pollutant emission and wind direction to model the pollutant exposure "dose" in the area surrounding each release site. It then adds a "toxicity weight" to each compound released, which represents its relative effect on human health in terms of cancer and non-cancer health outcomes. The RSEI geographic microdata then construct a "toxicity-weighted concentration," which accounts for both dose and toxicity weight and allows a comparison across geographic areas. These toxicity-weighted concentrations are then scaled on a national percentile in which all census tracts are ranked from 0 to 100 in order of toxicity-weighted concentration, with higher numbers reflecting higher levels of harmful toxic exposures.

The RSEI measure was chosen for several reasons. First, RSEI describes aggregate exposure to hundreds of toxic chemicals rather than focusing on individual pollutants. Those data more accurately model exposure to air pollution than does the simple linear distance to a point source (Chakraborty, Maantay, and Brender, 2011). Second, although the RSEI measure does not model the precise health impact of air pollution (for example, number of excess cancer cases per year), it serves as a screening tool that can describe general trends in burden of air pollution exposure. Third, RSEI models are released yearly, which allows for up-to-date estimates of local sources of air pollution. Area-level measures in the RSEI model are designed to be compared with each other across space and across time (EPA, 2021e). Fourth, the geographic microdata, including toxicity-weighted concentration, are available at the census tract level and can be easily merged with other census-tract level datasets. Finally, the releases relate to specific physical sites, which are identified in the EPA database. State LIHTC allocation agencies and LIHTC developers could locate those sites through the EasyRSEI dashboard and by their RSEI score to help make decisions about where to incentivize and propose new LIHTC properties (EPA, 2020).

Sensitivity analyses that compare this approach to that of Ellen, Horn, and Kuai (2018) use the HUD Affirmatively Furthering Fair Housing (AFFH) environmental health index (HUD PD&R, 2020). This index is constructed from the National Air Toxics Assessment (NATA), another commonly used environmental health index, which models the health risks from hazardous air pollutants (EPA, 2021c). These data model health risk from TRI industrial sites, as well as from mobile sources, such as cars and trucks. An important consideration is that NATA estimates may include different chemicals across years and are thus not intended to be compared across time periods. NATA estimates are also not intended to be compared across geographic areas but rather as a screening tool to highlight areas that may require further study. Higher values on the HUD AFFH environmental health index correspond to better air quality, to compare with other AFFH indices in which higher scores represent better neighborhood conditions, such as improved school quality or higher employment. For ease of comparison with the RSEI percentile, the HUD AFFH environmental health index was inverted so that higher scores on both indices represent increasing burden of air pollution. Ellen, Horn, and Kuai (2018) use the 2012 AFFH index, which uses data from the 2005 NATA release. Models were run with the 2012 AFFH index as well as the more recent 2018 index, based on the 2014 NATA release (HUD, 2020).

Neighborhood Characteristics

Census tract level variables were obtained from the American Community Survey 5-year estimates from 2014 through 2018 for all census tracts in the 50 states and Washington, D.C. Data were retrieved from the IPUMS National Historical Geographic Information System (Manson et al., 2020). Included are several groups of variables known to be associated with both LIHTC location and air pollution exposure. Those factors include data related to the housing market (median rent, percent renter occupancy, percent of rental units left vacant), factors related to socioeconomic status (percent unemployed and percent below federal poverty level), and demographic characteristics (percent Black residents and percent Hispanic residents). Population density and urbanicity are also included. Urbanicity was described using Rural-Urban Commuting Area (RUCA) codes, which categorize tracts on the basis of population density, urbanization, and commuting patterns within metropolitan areas (U.S. Department of Agriculture, Economic Research Service, 2020). Tracts were categorized as urban, suburban, large rural, or small rural (Washington State Department of Health, 2016).

Analysis Methods

The analysis began by describing differences between census tracts that contain LIHTC properties and census tracts that do not, using one-way analysis of variance or Chi^2 tests. Next, several logistic regression models were estimated in which the RSEI toxicity-weighted concentration nationally ranked percentile was the independent variable and the presence of any LIHTC property was the dependent variable. Each regression model included a fixed effect for the MSA in which each tract is located. For MSAs that cover multiple states, a fixed effect was used, which referred to the combination of MSA and state that applied to a given census tract. For adjusted models, covariates were added to the model by category of covariates (urbanicity, housing market characteristics, socioeconomic status, race and ethnicity). Thus, these models describe the independent association of industrial air pollution with the presence of LIHTC in a tract while controlling for variables that may be associated both with LIHTC location and burden of air pollution. The regression equation is shown below:

$$Log\ Odds(LIHTC) = \beta_0 + \beta_1 * RSEI_i + \beta_2 * X_i + \sigma_j + \varepsilon_j$$

In this equation, $LIHTC_i$ is an indicator variable for the presence or absence of at least one LIHTC unit in census tract *i*. $RSEI_i$ is the inverted nationally ranked percentile of the RSEI industrial air pollution toxicity-weighted concentration for a given census tract. β_0 is the intercept. β_1 is the regression coefficient; when exponentiated, this variable represents the odds ratio for each 10-percentile-point increase in the RSEI industrial air pollution score. β_2 is a vector of estimated coefficients, and X_i is an array of tract-level variables. σ_j is the state or MSA fixed effect. ε_j represents standard errors clustered by MSA. Results are presented as odds ratios, or the exponentiated forms of the coefficients in this equation.

In secondary analyses, separate unadjusted and fully adjusted regressions were run, in which the dependent variable was the presence of LIHTC units built in each of the three time periods (1987–1999, 2000–2007, 2008–2018). Separate regression models for each state and Washington, D.C., were run, to explore whether the relationship between industrial air pollution and the presence of LIHTC units differed across jurisdictions. For the final secondary analysis, the sample was restricted to those tracts that contain at least one LIHTC unit. This analysis used a linear regression model in which the dependent variable was the number of LIHTC units in the tract, and the independent variables were the RSEI percentile and covariates as described above. In this analysis, the dependent variable (number of LIHTC units) was highly positively skewed, so tracts with greater than 1,000 units were "top coded" (n=125, or 0.7 percent of all LIHTC tracts).

A series of sensitivity analyses were performed to explicitly compare the findings with those of Ellen, Horn, and Kuai (2018), which describes the differences in neighborhood conditions between LIHTC units and rental units in 12 states. First, the sample was limited to the LIHTC units that had been built in those 12 states in or before 2012. Next, a primary regression was performed (odds of LIHTC properties in the tract versus air pollution index) using four separate models, each using a different air pollution index as the independent variable: (1) the HUD environmental health index from 2012, as used by Ellen and colleagues; (2) an updated HUD environmental health index from 2018; (3) the RSEI index from 2012; and (4) the RSEI index from 2018 as used in the rest of this analysis. Then, the four models were estimated in the main sample, which includes all 50 states and all LIHTC units through 2018. The correlation coefficients between these four air pollution measures are also presented.

Finally, two other sensitivity analyses were included to test several assumptions in the modeling. Included first is a regression in which the independent variable is the RSEI measure categorized into quartiles, which allows a test of the assumption that the relationship between air pollution and the odds of LIHTC is linear. Second, a comparison was made between regressions in which the sample excludes tracts without multifamily units (the main cohort) versus regressions that include those tracts.

Results

LIHTC properties were found in 29 percent of metropolitan census tracts (exhibit 1). About one-fourth of LIHTC tracts had 50 units or less, whereas another one-fourth contained more than 200 units. Tracts with LIHTC properties differed in several key characteristics from tracts without LIHTC properties. Compared with non-LIHTC tracts, LIHTC tracts had higher proportions of Black residents (22.6 percent versus 12.3 percent, $p<0.001$) and Hispanic residents (20.1 percent versus 17.7 percent, $p<0.001$). Socioeconomic disadvantage was greater in LIHTC tracts, with an average poverty rate of 20.4 percent. LIHTC tracts were more densely populated and had greater proportions of renters (50.8 percent versus 35.7 percent, $p<0.001$). On a national level, LIHTC tracts in metropolitan areas experienced 1.7 percentile points higher industrial air pollution than non-LIHTC tracts (55.6 versus 53.9, $p<0.001$).

Exhibit 1

Bivariate Analysis of Census Tract Characteristics by Presence of LIHTC Properties

	Census Tracts With LIHTC Properties N (%) or Mean (SD)	**Census Tracts Without LIHTC Properties** N (%) or Mean (SD)
Total	16,406 (100%)	39,973 (100%)
Number of LIHTC Units per Tract		
1 to 50	4,437 (27.0%)	---
51 to 100	3,839 (23.4%)	---
101 to 200	4,103 (25.0%)	---
201+	4,027 (24.6%)	---
Population Density, in People per Mi^2	7,886 (16,028)	6,270 (12,297)
Urbanicity		
Urban	14,060 (85.7%)	34,792 (87.1%)
Suburban	1,299 (7.9%)	3,873 (9.7%)
Large Rural	590 (3.6%)	735 (1.8%)
Small Rural	457 (2.8%)	552 (1.4%)
Median Rent, in $	1,007 (372)	1,228 (485)
% Renter Occupied	50.8 (22.6)	35.7 (22.4)
% Vacancy	11.2 (8.5)	10.1 (9.4)
% Unemployment	7.7 (5.5)	5.9 (4.1)
% Below Poverty	20.7 (13.4)	13.0 (10.9)
% Black	22.6 (27.5)	12.3 (20.0)
% Hispanic	20.1 (23.8)	17.7 (21.8)
RSEI Industrial Air Pollution Percentile	55.6 (27.9)	53.9 (27.9)

LIHTC = Low-Income Housing Tax Credit. RSEI = Risk-Screening Environmental Indicators.

Notes: Includes all metropolitan tracts nationwide with >200 residents and multifamily housing. Sample includes metropolitan tracts nationwide with >200 residents and multifamily housing. All differences significant at p <0.01.

Sources: 2014–2018 American Community Survey 5-year estimates; LIHTC HUD User database; U.S. Department of Agriculture Economic Research Service Rural-Urban Community Area Codes; U.S. Environmental Protection Agency, Risk-Screening Environmental Indicators (RSEI) 2018 Model

Industrial air pollution was associated with the presence of LIHTC in a tract (exhibit 2). In the initial model, a 10-percentile-point increase in industrial air pollution was associated with 8-percent higher odds of LIHTC properties being located in that tract (OR 1.08, 95 percent CI [1.04, 1.12]).[1] This relationship was similar in the model that then adjusted for population density and urbanicity (OR 1.05, 95 percent CI [1.02, 1.09]). However, in the model that adjusted for housing market characteristics—including median rent, proportion of renters, and proportion of vacant properties—the relationship between industrial air pollution and the presence of LIHTC in a tract was inverted: a 10-percentile-point increase in industrial air pollution was significantly associated with lower odds of LIHTC properties being located in a tract (OR 0.96, 95 percent CI [0.93, 0.98]). The industrial air pollution percentile was not significantly associated with LIHTC in models that controlled for socioeconomic status or for those that accounted for area-level race and ethnicity. In the fully adjusted model, similar to the model adjusted only for housing market characteristics, a 10-percentile-point increase in industrial air pollution was associated with

[1] CI = confidence interval. OR = odds ratio.

5-percent lower odds of LIHTC properties being located in a tract, all else being equal (OR 0.95, 95 percent CI [0x.93, 0.98]).

Exhibit 2

Logistic Regression for Odds of LIHTC in a Tract Associated with a 10-Point Increase in RSEI Industrial Air Pollution Percentile

	Unadjusted	Urbanicity	Housing Market	Socioeconomic Status	Race & Ethnicity	Full Model
	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)
RSEI Industrial Air Pollution Percentile (10-point increase)	1.08*** (1.04, 1.12)	1.05*** (1.02, 1.09)	0.96*** (0.93, 0.98)	0.99 (0.96, 1.02)	0.97 (0.93, 1.01)	0.95** (0.93, 0.98)
Population Density, in 100 Persons/Mi²	---	1.00*** (1.00, 1.00)	---	---	---	1.00 (1.00, 1.00)
Urbanicity (ref: Urban)	---	Ref.	---	---	---	Ref.
- Suburban	---	0.77*** (0.69, 0.87)	---	---	---	1.22** (1.05, 1.41)
- Large Rural	---	1.91*** (1.67, 2.19)	---	---	---	2.01*** (1.71, 2.37)
- Small Rural	---	1.95*** (1.66, 2.29)	---	---	---	2.15*** (1.78, 2.59)
Median Rent, in $100	---	---	0.85*** (0.82, 0.88)	---	---	0.89*** (0.86, 0.92)
% Renters^	---	---	1.03*** (1.03, 1.03)	---	---	1.03*** (1.02, 1.03)
% Vacant^	---	---	1.00 (0.99, 1.00)	---	---	0.98*** (0.98, 0.99)
% Unemployment^	---	---	---	1.02*** (1.01, 1.03)	---	1.01 (1.00, 1.02)
% Below Poverty^	---	---	---	1.06*** (1.05, 1.06)	---	1.01*** (1.00, 1.01)
% Black^	---	---	---	---	1.03*** (1.03, 1.03)	1.01*** (1.01, 1.02)
% Hispanic^	---	---	---	---	1.02*** (1.02, 1.03)	1.00 (1.00, 1.01)
Number of Tracts	56,361	56,357	55,729	56,358	56,360	55,726

CI = confidence interval. OR = odds ratio. RSEI = Risk-Screening Environmental Indicators.

** p < 0.05. ** p < 0.01. *** p < 0.001.*

Notes: Sample includes metropolitan tracts nationwide with >200 residents and multifamily housing. All models include MSA fixed effects. ^ signifies change in odds ratio, ceteris paribus, associated with a 1-point increase in the independent variable from its mean.

Sources: 2014–2018 American Community Survey 5-year estimates; LIHTC HUD User database; U.S. Department of Agriculture Economic Research Service Rural-Urban Community Area Codes; U.S. Environmental Protection Agency, Risk-Screening Environmental Indicators (RSEI) 2018 Model

Several tract-level characteristics were also associated with the odds of LIHTC in the tract (exhibit 2). In fully adjusted models, suburban and rural tracts were more likely to contain LIHTC properties compared with urban tracts. Tracts with lower rents and a greater proportion of renters were more likely to contain LIHTC, whereas tracts with higher vacancy rates were less likely to contain LIHTC. Tracts with higher poverty rates and a greater proportion of Black residents were more likely to contain LIHTC properties, all else equal.

The point estimates of the relationship between present-day industrial air pollution and the odds of LIHTC development was relatively consistent across three periods in the history of the LIHTC program (exhibit 3). Similar to trends noted above for all LIHTC properties, tracts with higher industrial air pollution had higher odds of LIHTC development in the 2000–2007 and 2008–2018 periods. In addition, in models fully adjusted for neighborhood covariates, higher industrial air pollution was associated with lower odds of LIHTC development in the 1987–1999 and 2000–2007 periods.

Exhibit 3

Logistic Regression for Odds of LIHTC Built in One of Three Periods Associated with a 10-Point Increase in RSEI Industrial Air Pollution Percentile

	Unadjusted			Adjusted		
	1987–1999	2000–2007	2008–2018	1987–1999	2000–2007	2008–2018
	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)
RSEI Industrial Air Pollution Percentile (10-point increase)	1.05 (1.00, 1.10)	1.09*** (1.04, 1.14)	1.08*** (1.04, 1.13)	0.95* (0.92, 0.99)	0.96* (0.93, 1.00)	0.97 (0.94, 1.00)
Number of Tracts	56,138	56,206	56,138	55,505	55,572	55,505

CI = confidence interval. OR = odds ratio. RSEI = Risk-Screening Environmental Indicators.

** p < 0.05. ** p < 0.01. *** p < 0.001.*

Notes: Sample includes metropolitan tracts nationwide with >200 residents and multifamily housing. All models include MSA fixed effects. Adjusted models are controlled for population density, urbanicity, median rent, % renter, % vacant, % unemployment, % below poverty, % Black residents, and % Hispanic residents.

Sources: 2014–2018 American Community Survey 5-year estimates; LIHTC HUD User database; U.S. Department of Agriculture Economic Research Service Rural-Urban Community Area Codes; U.S. Environmental Protection Agency, Risk-Screening Environmental Indicators (RSEI) 2018 Model

Similar trends were seen when analyzing by individual states (exhibit A1). In general, most states had higher odds of LIHTC among more polluted tracts, and this relationship tended to be attenuated or reversed in adjusted models. In two states (NV and WA), however, LIHTC properties were more likely to be found in more polluted tracts, even when adjusting for neighborhood covariates.

Industrial air pollution was also associated with the number of LIHTC units among those tracts that contain at least one LIHTC unit (exhibit A2). A 10-percentile-point increase in industrial air pollution was associated with an increase of nearly 10 LIHTC units within a given MSA (beta 9.7, 95 percent CI [7.0, 12.5]). That relationship was no longer significant when accounting for neighborhood covariates, however (beta -0.6, 95 percent CI [-3.1, 0.8]).

In sensitivity analyses, similar trends to the main findings described above were observed when using the 2012 12-state sample from Ellen, Horn, and Kuai (2018) (exhibit 4); that is, higher levels of air pollution—using either the HUD environmental health index or RSEI industrial air pollution percentile from 2012 or 2018—were associated with increased odds of LIHTC in unadjusted models. As above, the direction of those relationships was reversed in the fully adjusted models.

Results using the full national sample and the four measures of pollution were similar to those found using the 12-state sample. Correlations across all four indices were positive and significant; correlations were stronger between 2012 and 2018 versions of the same index than correlations between the HUD index and the RSEI percentile (exhibit A3).

Exhibit 4

Logistic Regression for Odds of LIHTC in a Tract Associated with a 10-Point Increase in Air Pollution Percentile

	12-State Sample, 2012		Full National Sample, 2018	
	Unadjusted	Adjusted	Unadjusted	Adjusted
	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)
RSEI Percentile 2012	1.06* (1.01, 1.12)	0.95* (0.92, 0.99)	1.08** (1.03, 1.13)	0.96* (0.93, 0.98)
RSEI Percentile 2018^	1.07** (1.03, 1.12)	0.94*** (0.90, 0.97)	1.08*** (1.04, 1.12)	0.95** (0.93, 0.98)
HUD Index 2012^^	1.16*** (1.10, 1.23)	0.93*** (0.89, 0.97)	1.15*** (1.11, 1.18)	0.92*** (0.89, 0.94)
HUD Index 2018	1.19*** (1.12, 1.26)	0.97 (0.93, 1.01)	1.18*** (1.14, 1.22)	0.95** (0.91, 0.98)
Number of Tracts	27,372	27,083	56,354	55,722

CI = confidence interval. OR = odds ratio. RSEI = Risk-Screening Environmental Indicators.

^ Index used in current analysis.

^^ Index used in Ellen, Horn, and Kuai (2018).

$^{*}p < 0.05$. $^{**}p < 0.01$. $^{***}p < 0.001$.

Notes: Sample includes metropolitan tracts with >200 residents and multifamily housing. Outcome is presence of LIHTC units built in 2012 or earlier (12-state sample) or presence of LIHTC units built in 2018 or earlier (full national sample). All models include MSA fixed effects. Adjusted models are controlled for population density, urbanicity, median rent, % renter, % vacant, % unemployment, % below poverty, % Black residents, and % Hispanic residents.

Sources: 2014–2018 American Community Survey 5-year estimates; LIHTC HUD User database; U.S. Department of Agriculture Economic Research Service Rural-Urban Community Area Codes; U.S. Environmental Protection Agency, Risk-Screening Environmental Indicators (RSEI) Model

Analyses that categorized industrial air pollution in quartiles revealed similar results (exhibit A4). The odds of LIHTC increased monotonically with higher quartiles of industrial air pollution (OR 1.47, 95 percent CI [1.20, 1.80] for most polluted quartile, compared with least polluted quartile) in unadjusted models. In adjusted models, the effect size of the relationship with LIHTC also increased with increasing air pollution quartile. In other words, tracts with the highest burden of industrial air pollution had the lowest odds of LIHTC, when controlling for neighborhood characteristics. Finally, analyses that retained tracts without multifamily construction revealed similar results to the main findings that include only tracts with multifamily construction (exhibit A5).

Discussion

The findings indicate that, within a given metropolitan area, LIHTC properties are more likely to be found in tracts with poorer air quality. Although the specific health impact of this excess industrial air pollution burden is not known, a small difference between LIHTC and non-LIHTC neighborhoods could have important health implications when applied across millions of LIHTC residents nationwide. Indeed, small reductions in average PM2.5 levels have been associated with communitywide decreases in asthma exacerbation rates and cardiovascular mortality (Rajagopalan, Al-Kindi, and Brook, 2018; Simeonova et al., 2021). These findings add to the growing body of literature that describes the qualities of LIHTC neighborhoods and the complex relationships that exist among neighborhood features.

This finding aligns with previous work that suggested that LIHTC units are exposed to more air pollution than rental units overall within the same MSA (Ellen, Horn, and Kuai, 2018). Previous studies, however, presented associations that do not account for neighborhood-level covariates such as renter population, median rent, or neighborhood demographics, which may be associated with both air pollution burden and LIHTC development. The adjusted analysis in this study indicates that the direction of the relationship between air pollution and LIHTC location *reverses* when adjusting for those important covariates. This reversal of association between adjusted and unadjusted models was consistent even when applying the current model to the 12-state sample used in previous work and with different environmental health indices from multiple years.

In particular, housing market factors—including median rent, vacancy, and proportion of renters—may drive many LIHTC siting decisions, based on property values and rental demand, and those forces may have the undesired effect of locating LIHTC developments in more polluted neighborhoods overall. When local variations in housing markets are considered, LIHTC residents may experience somewhat *better* air quality when compared with residents of similar neighborhoods.

The findings from this study also show that, among neighborhoods with LIHTC, more polluted tracts were found to have higher numbers of LIHTC developments; however, that relationship was no longer significant when controlling for neighborhood covariates. Thus, LIHTC units may be more concentrated in polluted neighborhoods within a given MSA, but that circumstance may be due to other factors, such as neighborhood poverty level or housing market factors, which may promote larger or multiple developments within a given area. These findings suggest that, on balance, the burden of air pollution is disproportionate in areas in which LIHTC residents reside.

Consistent with previous research, this study found that LIHTC properties are more likely to be found in neighborhoods with a greater degree of poverty and unemployment (Ellen, Horn, and Kuai, 2018). LIHTC properties were in areas with lower median rents and higher concentrations of renters, which reflects the demand for low-cost rental properties in those areas. LIHTC properties were also more likely to be found in tracts with a higher proportion of Black residents, even after controlling for other neighborhood factors, such as socioeconomic status and housing market characteristics. The combination of higher exposure to industrial air pollution and higher proportion of Black residents in a neighborhood should motivate investigation into structural forces, such as housing segregation and environmental racism, which produce both poor quality housing and environmental harms in neighborhoods with low-income residents and people of color.

The spatial distribution of LIHTC should be considered in the context of complex funding priorities in Qualified Allocation Plans (QAPs). Although recent policy shifts are expanding the development of LIHTC properties in higher-income and suburban areas, multiple federal and state priorities over the program's history have concentrated properties in urban low-income neighborhoods. Other well-intentioned incentives within QAPs may also increase air pollution exposure, such as incentives awarded for locating LIHTC near employment or transit centers. The excess pollution risk experienced by workers of color living near industrial centers generally exceeds the excess employment benefit, however (Ash and Boyce, 2018), so developers should carefully evaluate those opposing forces when considering where to locate new properties. Developers must choose between maximizing the number of households that can be assisted by their properties and offering fewer units in areas where building is more expensive. When choosing between similar neighborhoods, developers likely prioritize areas that may be more appealing to potential tenants or that may face less resistance to development from local stakeholders. Many developers may choose to use LIHTC funds to modernize existing public housing developments. Because those properties are also more likely to be located in disadvantaged neighborhoods, developers may tend to concentrate LIHTC developments in areas with higher pollution exposure. Overall, many complex tradeoffs exist in deciding where LIHTC developments are built, and policy priorities that provide value in one area (transit access, proximity to community health centers, renovation of distressed housing) may bring about unintended or unavoidable consequences (neighborhood poverty, segregation, or air pollution exposure). Indeed, the definition of a "healthy neighborhood" is complex and may vary on the basis of the priorities and perceptions of its residents. In qualitative interviews with LIHTC tenants, residents recognize benefits (such as proximity to work, school, and cultural groups) and limitations (such as crime and pollution) of living in a neighborhood that may be considered impoverished or disadvantaged and often view their neighborhood more positively than objective measures of neighborhood quality might suggest (Reid, 2019). The current work suggests that developers and officials must consider air quality in relation to the range of factors when making decisions about where to prioritize housing credits.

These findings should be interpreted in the context of several limitations. Although this dataset is the most accurate source of LIHTC property data available, the data are reported to HUD by the programs and thus may be inaccurate or incomplete. This analysis describes average trends within MSAs; given that certain states have more expressly focused on building LIHTC in low-poverty areas, important variation likely exists between states or MSAs in the characteristics of LIHTC neighborhoods. State and local policymakers should consider how LIHTC and air pollution may be related in their specific jurisdiction. This analysis is not able to describe the timing of the placement of LIHTC developments compared with the timing of industrial development, although it attempts to demonstrate the relationship between phases of LIHTC development and present-day industrial air pollution. Industrial development may come before or after LIHTC construction, so this analysis shows the present results of decades of LIHTC siting decisions. For example, a new LIHTC property could be built near an existing industrial site, or a new industrial site could be built near an existing LIHTC property. In both situations, LIHTC residents are exposed to pollution, but the two scenarios would require different sets of policy solutions. For example, QAP disincentives could discourage building in areas with a high burden of pollution, whereas community organization and empowerment of LIHTC residents could prevent the construction of new pollution facilities in vulnerable neighborhoods. This analysis is unable to describe specific health consequences using these percentile-based environmental health indices, as it does not contain an inherent cutoff over which an area is considered "unsafe." The analyses do not account for spatial autocorrelation in the distribution of air pollution, LIHTC siting, or other neighborhood covariates, which are likely to be spatially dependent. Finally, this analysis does not include other important sources of pollution, such as traffic; the impact of industrial versus vehicular air pollution on LIHTC may be different given explicit priorities in some QAPs to locate LIHTC properties either away from highways or near transportation hubs. However, there were similar results when using the HUD AFFH environmental health index (based on the NATA index), which includes mobile sources of pollution, such as cars and trucks, in addition to stationary industrial sources.

Conclusions and Policy Recommendations

Overall, the findings of this study emphasize the importance of considering place when developing affordable housing. Local policymakers should consider how to use QAPs to prioritize building LIHTC properties in neighborhoods that promote the well-being of their residents. Recent initiatives to shift LIHTC development to high-opportunity neighborhoods show promise in locating LIHTC properties in lower poverty areas, which may carry an added benefit of decreasing air pollution exposure. Given the findings of this study, there are several suggested avenues for minimizing air pollution exposure while balancing the complex tradeoffs inherent in decision-making around LIHTC siting.

State QAPs can incentivize (or mandate) developers to provide a comprehensive summary of neighborhood conditions in areas where new properties are proposed. Notably, developments funded by HUD must comply with certain environmental justice standards and produce environmental assessments before receiving funding (Haberle, 2017). Those requirements do not necessarily apply to LIHTC properties, however, which are administered through the Department of the Treasury (Joint Center for Housing Studies of Harvard University, 2009). Although state LIHTC funding authorities often require such assessments, those environmental assessments or remediation efforts could be strengthened by mandatory enforcement, as in HUD programs.

Harmful exposures to pollution, however, should be considered alongside neighborhood assets, including access to schools, jobs, green space, healthy food, social support, and other opportunities. Some states, such as California, have expanded their emphasis on describing and incentivizing developments in high-opportunity neighborhoods (Reid, 2019). Beyond describing neighborhood conditions, states can also commission Health Impact Assessments to characterize the health benefits or risks of developing in a particular area. QAPs can use these data to explicitly prioritize development in health-promoting neighborhoods, recognizing that tradeoffs and balances among different factors may exist (for example, locating close to transportation hubs versus less dense neighborhoods). Finally, given that households living in LIHTC properties may experience less industrial air pollution compared with other, similar neighborhoods, more research is needed to understand the specific mechanisms within QAPs that produce this benefit. Much of that analysis will be most meaningful if conducted at a state or local level to understand how the national findings apply to the housing markets and policy landscapes in each jurisdiction.

In addition to housing agencies, other stakeholders can take steps to reduce pollution exposure among LIHTC residents. Although the implications of those findings for the siting of new industrial facilities is beyond the scope of this current study, policies can be considered which limit the development of polluting facilities in close proximity to existing LIHTC properties or other federally assisted housing. Enhanced coordination between HUD, LIHTC, and EPA can ensure that local housing agencies (and their tenants) are informed about environmental concerns (Coffey et al., 2020). Overall, governmental agencies, advocacy organizations, and community members should work in concert to limit the disproportionate burden of air pollution and other environmental harms on federally assisted households.

Appendix

Exhibit A1

Logistic Regression for Odds of LIHTC in a Tract Associated with a 10-Point Increase in RSEI Industrial Air Pollution Percentile (1 of 2)

State	Unadjusted	Adjusted	Number of Tracts
	OR	OR	
AK	1.41***	0.99	92
AL	0.97	0.99	734
AR	1.06	0.84*	365
AZ	1.11**	0.98	1,163
CA	1.02	0.88***	7,236
CO	1.13	1.09	938
CT	1.16	0.87	738
DC	0.79	1.11	175
DE	1.20	0.84***	190
FL	1.12**	0.96	3,721
GA	0.99	1.01	1,326
HI	1.28***	0.93	258
IA	1.07	0.89	433
ID	0.98	0.94	190
IL	1.05	0.92	2,562
IN	1.15***	1.04	1,057
KS	0.90*	0.90	437
KY	1.03	0.93	578
LA	0.91**	0.88	841
MA	1.01	0.90*	1,400
MD	1.14**	0.91*	1,190
ME	1.30***	1.08	183
MI	1.04	0.92	1,991
MN	1.03	0.93	920

Exhibit A1

Logistic Regression for Odds of LIHTC in a Tract Associated with a 10-Point Increase in RSEI Industrial Air Pollution Percentile (2 of 2)

State	Unadjusted	Adjusted	Number of Tracts
MO	1.10***	0.86	942
MS	1.01	0.97	261
MT	1.26	1.03	81
NC	1.13*	1.00	1,493
ND	1.81***	1.40	74
NE	1.24	0.93	289
NH	1.91***	1.33	165
NJ	1.07**	0.93**	1,864
NM	1.20	0.77***	272
NV	1.22*	1.10*	549
NY	1.26	0.97	4,270
OH	1.12	0.99	2,277
OK	0.88***	1.02	592
OR	1.05	0.94	627
PA	1.13*	1.00	2,700
RI	1.08	1.12	237
SC	0.96	1.00	785
SD	1.59**	1.13	82
TN	1.14**	1.04	1,027
TX	1.06	0.98	4,017
UT	0.91*	0.93	476
VA	1.20***	0.95	1,377
VT	0.19	0.028	37
WA	1.23***	1.17*	1,181
WI	1.04	0.85*	993
WV	0.96	1.01	286
WY	2.37*	1.20	33

CI = confidence interval. OR = odds ratio.

** $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.*

Notes: Sample includes metropolitan tracts with >200 residents and multifamily housing. All models include MSA fixed effects. Adjusted models are controlled for population density, urbanicity, median rent, % renter, % vacant, % unemployment, % below poverty, % Black residents, % Hispanic residents.

Sources: 2014–2018 American Community Survey 5-year estimates; LIHTC HUD User database; U.S. Department of Agriculture Economic Research Service Rural-Urban Community Area Codes; U.S. Environmental Protection Agency, Risk-Screening Environmental Indicators (RSEI) 2018 Model

Exhibit A2

Linear Regression for Number of LIHTC Units in a Tract Associated with a 10-Point Increase in RSEI Industrial Air Pollution Percentile

	Unadjusted	Full Model
	Beta (95% CI)	Beta (95% CI)
RSEI Industrial Air Pollution Percentile (10-point increase)	9.7*** (7.0, 12.5)	-0.6 (-3.1, 1.8)
Population Density, in 100 Persons/mi²	---	-0.02 (-0.07, 0.03)
Urbanicity (ref: Urban)	---	Ref.
- Suburban	---	-22.2*** (-31.1, -13.3)
- Large Rural	---	-10.8 (-23.3, 1.64)
- Small Rural	---	-23.3*** (-36.0, -10.5)
Median Rent, in $100	---	-2.2 (-4.7, 0.3)
% Renters^	---	2.2*** (1.9, 2.5)
% Vacant^	---	-2.9*** (-3.5, -2.3)
% Unemployment^	---	-0.9* (-1.6, -0.2)
% Below Poverty^	---	0.4 (-0.1, 0.8)
% Black^	---	0.5*** (0.3, 0.8)
% Hispanic^	---	-0.5** (-0.9, -0.2)
Number of Tracts	16,406	16,357

CI = confidence interval. RSEI = Risk-Screening Environmental Indicators.

^ signifies change in odds ratio, ceteris paribus, associated with a 1-point increase in the independent variable from its mean.

** p < 0.05. ** p < 0.01. *** p < 0.001.*

Notes: Sample includes metropolitan tracts nationwide with >200 residents and multifamily housing that contains at least one LIHTC property. All models include MSA fixed effects. Betas correspond to the change in number of LIHTC units in a tract per change in independent variable.

Sources: 2014–2018 American Community Survey 5-year estimates; LIHTC HUD User database; U.S. Department of Agriculture Economic Research Service Rural-Urban Community Area Codes; U.S. Environmental Protection Agency, Risk-Screening Environmental Indicators (RSEI) 2018 Model

Exhibit A3

Correlation Coefficients Between Air Pollution Percentile Indices

	RSEI Percentile 2012	RSEI Percentile 2018	HUD Index 2012	HUD Index 2018
RSEI Percentile 2012	--	--	--	--
RSEI Percentile 2018	0.85***	--	--	--
HUD Index 2012	0.25***	0.20***	--	
HUD Index 2018	0.36***	0.32***	0.66***	--

RSEI = Risk-Screening Environmental Indicators.

**** $p < 0.001$.*

Notes: Higher scores on each air pollution index indicates higher burden of air pollution. HUD index used here is inverted from original form, so that higher values correspond to higher pollution. Sample includes metropolitan tracts with >200 residents and multifamily housing.

Sources: HUD, Affirmatively Furthering Fair Housing (AFFH) Opportunity Indices; U.S. Environmental Protection Agency, Risk-Screening Environmental Indicators (RSEI) 2018 Model

Exhibit A4

Logistic Regression for Odds of LIHTC in a Tract Associated with Increasing Quartiles of Risk-Screening Environmental Indicators (RSEI) Industrial Air Pollution Percentile

	Unadjusted	Full Model
RSEI Industrial Air Pollution Percentile	OR (95% CI)	OR (95% CI)
Quartile 1 (0–25%)	Ref.	Ref.
Quartile 2 (25–50%)	1.19* (1.01, 1.40)	0.96 (0.83, 1.10)
Quartile 3 (50–75%)	1.20 (0.97, 1.48)	0.84* (0.71, 0.99)
Quartile 4 (75–100%)	1.47*** (1.20, 1.80)	0.77** (0.63, 0.93)
p-Value for Trend	<0.001	-0.007
Number of Tracts	56,361	55,726

CI = confidence interval. RSEI = Risk-Screening Environmental Indicators. OR = odds ratio.

** $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.*

Notes: Sample includes metropolitan tracts nationwide with >200 residents and multifamily housing. All models include MSA fixed effects. Adjusted models are controlled for population density, urbanicity, median rent, % renter, % vacant, % unemployment, % below poverty, % Black residents, % Hispanic residents.

Sources: 2014–2018 American Community Survey 5-year estimates; LIHTC HUD User database; U.S. Department of Agriculture Economic Research Service Rural-Urban Community Area Codes; U.S. Environmental Protection Agency, Risk-Screening Environmental Indicators (RSEI) 2018 Model

Exhibit A5

Logistic Regression for Odds of LIHTC in a Tract, Given a 10-Point Increase in RSEI Industrial Air Pollution Percentile

	Unadjusted (all metro tracts)	Unadjusted (multifamily only)	Full Model (all metro tracts)	Full Model (multifamily only)
	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)
RSEI Industrial Air Pollution Percentile (10-point increase)	1.10*** (1.06, 1.14)	1.08*** (1.04, 1.12)	0.96** (0.93, 0.98)	0.95** (0.93, 0.98)
Population Density, in 100 Persons/Mi^2	---	---	1.00 (1.00, 1.00)	1.000 (0.999, 1.001)
Urbanicity (ref: Urban)	---	---	Ref.	Ref.
- Suburban	---	---	1.08 (0.94, 1.25)	1.22** (1.05, 1.41)
- Large Rural	---	---	1.96*** (1.67, 2.30)	2.01*** (1.71, 2.37)
- Small Rural	---	---	1.99*** (1.66, 2.39)	2.15*** (1.78, 2.50)
Median Rent, in $100	---	---	0.88*** (0.85, 0.92)	0.89*** (0.86, 0.92)
% Renters^	---	---	1.03*** (1.02, 1.03)	1.03*** (1.02, 1.03)
% Vacant^	---	---	0.98*** (0.98, 0.99)	0.98*** (0.98, 0.99)
% Unemployment^	---	---	1.01 (1.00, 1.01)	1.01 (1.00, 1.02)
% Below Poverty^	---	---	1.01** (1.00, 1.01)	1.01*** (1.00, 1.01)
% Black^	---	---	1.01*** (1.01, 1.02)	1.01*** (1.01, 1.02)
% Hispanic^	---	---	1.00 (1.00, 1.01)	1.00 (1.00, 1.01)
Number of Tracts	60,220	56,361	59,157	55,726

CI = confidence interval. RSEI = Risk-Screening Environmental Indicators. OR = odds ratio.

** p < 0.05. ** p < 0.01. *** p < 0.001.*

^ signifies change in odds ratio, ceteris paribus, associated with a 1-point increase in the independent variable from its mean.

Notes: Sample includes metropolitan tracts with >200 residents and multifamily housing. All models include MSA fixed effects.

Sources: 2014–2018 American Community Survey 5-year estimates; LIHTC HUD User database; U.S. Department of Agriculture Economic Research Service Rural-Urban Community Area Codes; U.S. Environmental Protection Agency, Risk-Screening Environmental Indicators (RSEI) 2018 Model

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Departments

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Data Shop

Data Shop, a department of Cityscape, *presents short articles or notes on the uses of data in housing and urban research. Through this department, the Office of Policy Development and Research introduces readers to new and overlooked data sources and to improved techniques in using well-known data. The emphasis is on sources and methods that analysts can use in their own work. Researchers often run into knotty data problems involving data interpretation or manipulation that must be solved before a project can proceed, but they seldom get to focus in detail on the solutions to such problems. If you have an idea for an applied, data-centric note of no more than 3,000 words, please send a one-paragraph abstract to chalita.d.brandly@hud.gov for consideration.*

Rural Definitions Matter: Implications for HUD Assistance Programs

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The views expressed in this article are those of the author and do not represent the official positions or policies of the Office of Policy Development and Research, the U.S. Department of Housing and Urban Development, or the U.S. government.

Abstract

Multiple definitions of rural areas are used in the federal government. Although one universal definition of rural *does not exist, the choice of definition used for a particular government program or researcher depends on the various geographies and population, different aspects of rurality in terms of socioeconomic characteristics, and purpose of intervention. Using the U.S. Department of Housing and Urban Development (HUD) administrative data, the author investigates how some of the most commonly used rural classifications could affect the number, demographic, and economic characteristics of the HUD-assisted population in major assistance programs in rural areas as a consequence of those differences in definition. This article analyzes the differences by definition, degrees of overlapping areas, and rural HUD coverage then investigates selected demographic and economic differences among HUD-assisted rural households by diverse rural definitions. Whereas the size of the HUD-assisted population varies greatly depending on the rural definition, demographic characteristics appear more consistent with each other; however, economic characteristics display more variability by varying definitions. Understanding the differences in assisted populations could provide valuable insights to researchers and policymakers to identify a definition of* rural *best suited for specific purposes.*

Introduction

Researchers, policymakers, and communities in the United States often struggle to define what is rural. Definitions of *rural* have a profound effect on regional socioeconomic and health development in the United States because federal programs and other funding institutions have strict eligibility criteria to qualify for rural programs and assistance. As the United States has progressed from a mainly agricultural society to an industrialized one, the urban population has drastically grown, sprawling farther outward from cities and major labor markets. The U.S. Census Bureau estimates that approximately 20 percent of all Americans reside in rural areas, which encompass 75 percent of the total U.S. landmass (U.S. Census Bureau, 2017). However, depending on which rural definition is used, the rural population estimates could range from 17 to 49 percent (Cromartie and Bucholtz, 2008). Different federal agencies and departments using different criteria for rural areas could add further confusion and profoundly affect the size and location of the U.S. population they are trying to serve.

A fundamental challenge to understanding rural America lies with the multidimensional aspect of rurality. Although many researchers and policymakers would like to have one standardized definition of rural that fits all of their needs, they have never been in complete agreement and are not likely to agree in the future. Some of the major considerations in defining rural include population size and density, adjacency to urbanized cores, commuting patterns to big cities, political borderlines and geographical units, and data availability.

Two definitions serve as foundational building blocks for many other rural definitions: one from the Census Bureau, with emphasis on land use for residential purposes, and the other from the Office of Management and Budget (OMB), with emphasis on the labor market (Isserman, 2007; Slifkin, Randolph, and Ricketts, 2004). On the basis of the decennial census, the Census Bureau defines rural in terms of nonurbanized areas or clusters at the census block and block group level, whereas OMB does not define rural areas at all. Instead, OMB defines metropolitan (metro) and nonmetropolitan (nonmetro) counties for statistical purposes only[1] (U.S. Census Bureau, 2021a). Much confusion and complication arise when media, researchers, and policymakers—against OMB's guidance—commonly refer to nonmetro counties as "rural counties," which greatly differ from "rural areas" by the Census Bureau (Pipa and Geismar, 2021; Porter et al., 2004; USDA, 2005). Approximately 40 percent of the nonmetro county population lives in urban areas, as defined by the Census Bureau, whereas almost 50 percent of the rural population lives in metro counties, as defined by OMB (Cromartie and Bucholtz, 2008). This variation implies that if program assistance and funding eligibility criteria are based on nonmetro county status, many rural people or communities within metro counties would not qualify. Because most federal, state, and other regional definitions of rural stem from the definitions of those two entities, with emphasis on different aspects of rurality, the divergence between various rural definitions is unavoidable.

Another complicating matter in defining rural areas is the fluid aspect of defining rural and nonmetro areas by the Census Bureau and OMB themselves. Although they have been updating the rural and nonmetro areas after each decennial census, they have determined lately to drastically

[1] Although OMB recognizes that a number of agencies use the delineation for nonstatistical programmatic applications, OMB does not take nonstatistical uses into consideration or make modifications because of them.

change the standards for delineating urban areas or clusters and nonmetro counties, respectively (OMB, 2021; U.S. Census Bureau, 2022). The OMB proposal to increase the minimum core population threshold for metropolitan statistical areas (MSAs) could result in an increased number of large nonmetro counties with better socioeconomic characteristics, potentially competing with small, poverty-stricken communities for federal funding earmarked for rural areas or receiving special considerations due to their "rural county" status by OMB-based rural eligibility criteria (Pipa and Geismar, 2021). In a similar way, the Census Bureau's *Urban Area Criteria for the 2020 Census—Final Criteria*, based on the 2020 decennial census, would reclassify hundreds of urban areas as nonurban (rural). Federal and state programs with rural eligibility criteria would need to reallocate their resources accordingly, potentially decreasing the funding amount in currently designated rural areas.

This article investigates how various definitions of rural areas could affect the size and socioeconomic characteristics of the assisted population. Using administrative data at HUD, this article aims to compare the magnitude and characteristics of the HUD-assisted population according to various rural definitions. Although some researchers have focused on the differences in population size and characteristics using American Community Survey (ACS) data at the census tract level, to this author's knowledge, this article is the first such work analyzing nationwide federal programs and their assisted populations at the census block level. The author investigates whether applying different rural definitions significantly alters the size and characteristics of the HUD-assisted population in rural areas and explores how many HUD-assisted individuals are left out because of different rural considerations. This finding could provide researchers and policymakers valuable insight into how defining rural areas could have a significant effect on who is assisted and where.

The rest of this article is organized in the following order. First, the article describes the HUD administrative dataset and various rural classifications used in the analysis. Then, the author discusses the analytical methodology used, followed by the results. The article concludes with discussion and policy implications.

Data and Methods

HUD Administrative Data

This article uses HUD administrative data to describe the characteristics of rural households and individuals receiving HUD housing assistance.[2]

Analysts used a December 2019 extract standardized across two HUD administrative databases: the Public and Indian Housing (PIH) Information Center (PIC) and the Tenant Rental Assistance Certification System (TRACS).[3] Those databases contain programmatic information collected by HUD-affiliated housing providers (that is, local public housing agencies or private multifamily

[2] Only U.S. households with geographic information at the census tract level (excluding the U.S. territories) are considered for analysis.

[3] Prepandemic (COVID-19) data are used to avoid complications with data verification issues. For the purpose of the analysis, HUD administrative data from December 2019 are sufficient to illustrate the differences among various rural classification systems.

building owners) on HUD forms 50058, 50058-MTW, 50059, and 50059-A. The extract captures information about households and individuals who received housing rental assistance during the previous 36 months for Moving to Work (MTW) agencies and the previous 18 months for TRACS and non-MTW agencies. End-of-participation records were excluded because households ending participation are not considered active. The author identified approximately 9 million HUD-assisted individuals with full geographical information for the rural definitions.

Rural Definitions

For this article, six rural classifications were applied to HUD-assisted populations by the Census Bureau, OMB, U.S. Department of Agriculture (USDA), Health Resources and Services Administration (HRSA), and HUD. They include three dichotomous (Census Bureau, OMB, and HRSA), one trichotomous (HUD's Urbanization Perceptions Small Area Index [UPSAI]), and two continuous (USDA's rural-urban commuting area [RUCA] 1 and 2) area classifications.[4] Five rural classifications were chosen for their frequent usage and recognition among researchers, communities, and policymakers on federal funding eligibility criteria. Although UPSAI is a perception classification and has not been used for any programming purposes, it was chosen to reflect the residents' assessment of their neighborhood and to compare with other rural classifications, especially in the HUD program areas.

The following section illustrates how each rural classification system is defined and used in the article; exhibit 1 summarizes them. Although other definitions of rural are commonly used, most of them are based on either the Census Bureau definition or OMB classification of metro and nonmetro counties (Coburn et al., 2007). For instance, other commonly used rural definitions, such as Rural-Urban Continuum Code (RUCC) and Urban Influence Code (UIC), delineate a spectrum of rurality into 9 codes and 12 codes, respectively, at the county level based on OMB metro-nonmetro county classification. If those areas were reclassified as dichotomous urban-rural, they would be very similar to the OMB definition of metro-nonmetro.

[4] Because the article analyzes urban-rural dichotomy, it does not examine definitions or influences of suburban areas. As such, UPSAI are categorized as either urban or rural on the basis of the author's reclassification scheme.

Exhibit 1

Rural Classifications (1 of 2)

Rural Classification Basis	Agency	Base Year/ Data Source	Updates	Dichotomy	Geographical Level	Categorization	Rural/Urban Description	Strength	Weakness
Urbanized Areas/Urban Clusters (UAs/UCs)	Census Bureau	2010 Decennial Census	Decennial	Dichotomous	UA/UC (Census Blocks and Block Groups)	UAs/UCs as urban; everywhere else considered rural	Rural identified as not UAs/UCs (UAs: 50,000 or more; UCs: at least 2,500 but less than 50,000)	1. The most precise geographical unit 2. Easy to understand population/density threshold	1. No consideration for political/ governing boundaries 2. Census blocks/ block groups not commonly used in policy implementation or research
Core-Based Statistical Areas (CBSAs)	OMB	2010 Decennial Census	Periodic[a] (new population estimates but decennial-updated commuting-to-work data)	Dichotomous	County	Metropolitan Statistical Area, Micropolitan Statistical Area, Non-Core Area	Rural commonly identified as nonmetro areas (micro- and non-core counties), where metro areas contain core urban areas of 50,000 or more	1. Easy to interpret county boundaries as political boundaries 2. Easy to be used by policymakers (resource distribution) and researchers (data availability for analysis)	1. Not intended for rural classification 2. Substantial variation in size among counties 3. Both urban and rural areas included in larger counties
Rural-Urban Commuting Areas (RUCA)	USDA	2010 Decennial Census + 2006–2010 ACS	Decennial	Multilevel	Census Tract	Degrees of Rurality (10 primary codes and 30 secondary codes, using measures of population density, urbanization, and daily commuting)	1. Rural commonly identified with primary RUCA 4–10 (nonmetro areas), or 2. Rural identified with primary RUCA 2,3,5,6,8,9,10 (nonurban core)	1. More precise classification of urban-rural spectrum 2. Easy to compare more/less rural areas	1. Too complex/ precise delineation of urban-rural continuum into many codes 2. Several ways to define rural using different combinations of codes

Exhibit 1

Rural Classifications (2 of 2)

Rural Classification Basis	Agency	Base Year/ Data Source	Updates	Dichotomy	Geographical Level	Categorization	Rural/Urban Description	Strength	Weakness
Federal Office of Rural Health Policy (FORHP)	HRSA	OMB + RUCA	Periodic[b]	Dichotomous	County, Census Tract	Rural as defined; everywhere else considered urban	Rural identified as 1. nonmetro counties, 2. metro census tracts, with RUCA (4–10), 3. census tracts at least 400 sq. miles, with population density of 35 or fewer per sq. mile, with RUCA (2,3)	1. Inclusion of rural tracts in metro counties as rural 2. Inclusion of large RUCA metro tracts with small population density as rural	1. Complex rural definition 2. Policy-and funding-oriented definition 3. Not discounting urban areas in nonmetro counties
Federal Office of Rural Health Policy (FORHP)	HRSA	OMB + RUCA	Periodic[b]	Dichotomous	County, Census Tract	Rural as defined; everywhere else considered urban	Rural identified as 1. nonmetro counties, 2. metro census tracts, with RUCA (4–10), 3. census tracts at least 400 sq. miles, with population density of 35 or fewer per sq. mile, with RUCA (2,3)	1. Inclusion of rural tracts in metro counties as rural 2. Inclusion of large RUCA metro tracts with small population density as rural	1. Complex rural definition 2. Policy- and funding-oriented definition 3. Not discounting urban areas in nonmetro counties
Urbanization Perceptions Small Area Index (UPSAI)	HUD[c]	2017 AHS	One-Time[d]	Trichotomous	Census Tract	Urban, suburban, rural (perceived by respondents)	Rural identified as 1. perceived as rural by respondents, 2. Suburban tracts redefined by author as rural if (a) rural perception is greater, for tracts with suburb perception of less than 80%; (b) RUCA (4–10) for tracts with suburb perception of greater than 80%	1. Perception of real people about their neighborhood 2. Inclusion of suburban category	1. Hard to fit suburb into urban-rural classification 2. Perception does not have absolute standards and could vary wildly by each individual

ACS = American Community Survey. AHS = American Housing Survey. CBSA = Core-Based Statistical Areas. FORHP = Federal Office of Rural Health Policy. HRSA = Health Resources and Services Administration. OMB = Office of Management and Budget. RUCA = rural-urban commuting area. UA= Urbanized Area. UC = Urban Cluster. UPSAI = Urbanization Perceptions Small Area Index. USDA = U.S. Department of Agriculture.

[a]OMB-CBSA: Between censuses, the delineations are revised to reflect Census Bureau population estimates and commuting-to-work data. Based on 2010 standards and Census Bureau data, areas were first delineated in February of 2013.

[b]HRSA-FORHP: Beginning with Fiscal Year (FY) 2022, rural definition will include additional outlying metro counties without a UA and will not remove any previously rural-designated counties.

[c]HUD does not use UPSAI in any official or programmatic manner.

[d]HUD-UPSAI: Update of UPSAI is planned once the 2023 AHS data become available.

Sources: (By rural classification basis) UA/UC—U.S. Census Bureau (2021b); CBSA—U.S. Census Bureau (2021a); RUCA—USDA (2020); HRSA-FORHP—HRSA (2022); UPSAI—HUD (2020)

Census Bureau Definition

The Census Bureau does not define rural directly; instead, it identifies urban areas, and whatever is not included in urban areas is considered rural. The Census Bureau's official definition of urban in the early 20th century identified incorporated cities and towns with at least 2,500 people as urban places (Ratcliffe et al., 2016). Since then, the Census Bureau has continued to revise its definition of urban to reflect the changes in population and population density in the United States. Using census blocks and block groups as the primary geographical units for urban areas, the Census Bureau revises urban areas on the basis of each decennial census.

The Census Bureau identifies two types of urban areas on the basis of total population thresholds, density, and land use: Urbanized Areas (UAs) with 50,000 or more people and Urban Clusters (UCs) with at least 2,500 and fewer than 50,000 people. Rural, then, is defined as all population, housing, and territory not included in UAs or UCs. For a full description, refer to https://www.census.gov/programs-surveys/geography/guidance/geo-areas/urban-rural/2010-urban-rural.html.

Office of Management and Budget Classification

OMB does not define urban or rural areas at all. Instead, OMB defines and periodically updates Core-Based Statistical Areas (CBSAs) on the basis of the Census Bureau urban definition, commuting patterns, economic integration, and proximity to metropolitan counties to support consistent data collection and sharing among federal agencies (Coburn et al., 2007). By including work commuting patterns, metro areas represent labor market areas beyond UA or UC cores (Bennett et al., 2019).

The OMB classification of U.S. counties based on MSAs and non-MSAs has been widely used by programs, communities, and researchers as an alternative to the Census Bureau's urban-rural definition (Coburn et al., 2007). However, OMB cautions against such practice, as its delineation of counties is for statistical purposes only (Coburn et al., 2007). OMB defines metro areas as (1) central counties with one or more UAs and (2) outlying counties with economic ties to the core counties, as measured by work commuting (if at least 25 percent of workers living in the county commute to the central counties or at least 25 percent of the employment in the county consists of workers coming from the central counties). The rest of the counties are categorized as nonmetro counties. This article follows the widely used practice of categorizing nonmetro counties as "rural" counties. For a full description, refer to https://www.census.gov/programs-surveys/metro-micro/about.html.

Rural-Urban Commuting Area (U.S. Department of Agriculture-Economic Research Service) Classification

The Economic Research Service (ERS) at USDA has several nondichotomous definitions of rural areas. Rather than strictly defining urban-rural areas, ERS uses a spectrum of rurality. One of the most commonly used rural definitions by researchers (other than the Census Bureau and OMB) is RUCA codes. The RUCA codes categorize U.S. Census tracts into 10 primary codes and 30 secondary codes, using measures of population density, urbanization, and daily commuting.

Although similar in concept to the OMB classification of county-level metropolitan (metro) and nonmetropolitan (nonmetro) areas, RUCA codes identify urban cores and adjacent territories by using census tracts as geographical building blocks to differentiate degrees of rurality, ranging from the core of urbanized areas (RUCA 1) to isolated, small rural areas (RUCA 10). Census tracts, equivalent of urban areas, are defined as metropolitan areas and classified as Codes 1, 2, and 3. Census tracts, the equivalent of urban clusters, are defined as micropolitan and small town cores and classified as Codes 4 and 7, respectively. RUCA codes were chosen as a means to analyze rural geography because they describe every census tract in the United States, allowing researchers to identify rural areas in metropolitan counties, urban areas in micropolitan counties, and small-town areas (Hart, Larson, and Lishner, 2005). To create a dichotomous urban-rural classification, the author uses two sets of rural delineations based on RUCA codes. First, this article follows a commonly used guideline in literature and identifies census tracts with RUCA codes 1, 2, and 3 (metropolitan areas) as urban and the rest as rural (Long, Delamater, and Holmes, 2021) and refers to this rural classification as RUCA1. Second, the article uses an alternative strategy of delineating RUCA codes 1, 4, and 7 (urban core areas with primary commuting flows) as urban and the rest as rural and refers to it as RUCA2. Whereas RUCA1 uses a similar strategy to OMB's metro-nonmetro classification, RUCA2 is closer to the Census Bureau urban-rural classification using RUCA codes. For a full description of each primary RUCA code, refer to https://www.ers.usda.gov/data-products/rural-urban-commuting-area-codes/documentation/.

Health Resources and Services Administration Definition

The Federal Office of Rural Health Policy (FORHP) at the Health Resources and Services Administration (HRSA) uses its own definition of rural for the purpose of eligibility criteria for its rural programs. Using ERS's RUCA codes as a foundational structure, FORHP includes additional consideration for distance to health services and a low number of people being served on certain large census tracts. Thus, HRSA defines rural areas as (1) all nonmetro counties; (2) all census tracts in metro counties with RUCA codes 4–10; and (3) large area census tracts (at least 400 square miles in area, with a population density of 35 or fewer per square mile) with RUCA codes 2–3. For a full description, refer to https://www.hrsa.gov/rural-health/about-us/what-is-rural.

Urbanization Perceptions Small Area Index (HUD) Perception Classification

Although the majority of the assistance programs at HUD do not include rurality as their eligibility criteria, several rural-specific capacity-building programs adhere to the Census Bureau's rural definition for funding eligibility (HUD, n.d.). Although not defining its own criteria for urban and rural areas, HUD created UPSAI, which classifies U.S. census tracts as urban, suburban, or rural on the basis of a neighborhood perception survey that was part of the 2017 American Housing Survey (AHS). When the 2017 AHS was conducted, more than one-half (52 percent) of all respondents described their neighborhood as suburban, 27 percent as urban, and 21 percent as rural (Bucholtz, Molfino, and Kolko, 2020). To compare the HUD perception index with other rural classifications, suburb is recategorized as either urban or rural. When UPSAI categorizes a census tract as a suburb, the author attempted to (1) reclassify it as urban or rural, whichever was perceived more, for suburb perception of less than 80 percent; or (2) reclassify it as urban or rural, following the RUCA1 classification, for suburb perception of greater than 80 percent.[5] For a full description, refer to https://www.huduser.gov/portal/AHS-neighborhood-description-study-2017.html#small-area-tab.

Methodology

The author applied various rural classifications to HUD-assisted individuals and their residences using HUD program administrative data. The dataset includes the recipients of various HUD assistance programs, including Housing Choice Voucher (HCV), Project-Based Section 8, and public housing—the three largest programs at HUD. Whereas definitions of rural have previously been used to categorize the U.S. population using the Census Bureau data (Long, Delamater, and Holmes, 2021; Ricketts, Johnson-Webb, and Taylor, 1998), this is the first time the locations of federal program participants were analyzed by various urban-rural classifications. Unlike the Census Bureau data, HUD administrative data could not only illustrate the different recipient characteristics among the classifications, but it could also reflect the areas of specific programming focus. First, the author calculated the number of HUD-assisted individuals identified as residing in rural areas by each rural classification scheme and evaluated the size of the overlapping assisted population, providing a foundation for the degree of agreement between various classifications. Then, the author investigated the differences between HUD-assisted populations of each rural classification by comparing demographic characteristics such as gender, race and ethnicity, seniors, and people with disabilities, and also by comparing household income, income sources, and HUD assistance program participation status.

Results

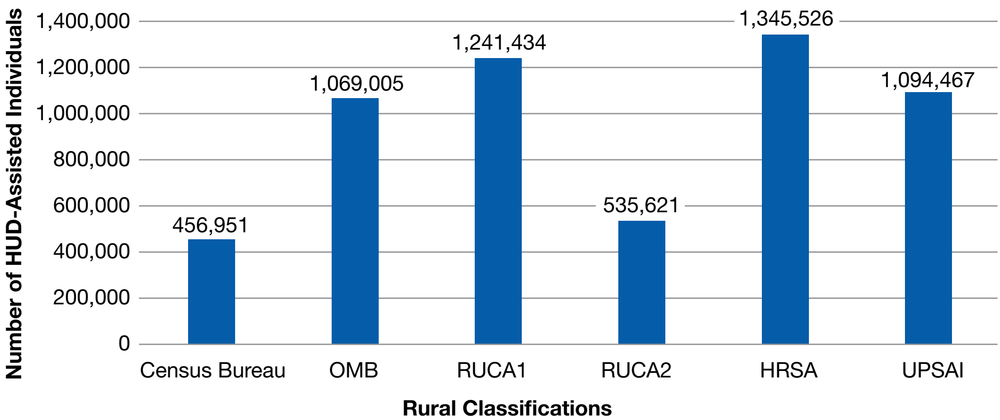
Exhibit 2 illustrates the number of HUD-assisted individuals by each rural classification. Approximately 10 million individuals were served by various HUD programs (excluding those in U.S. territories). Among them, approximately 1.07 million people resided in nonmetro counties, by OMB classification, whereas about 460,000 resided in rural areas, by Census Bureau definition. Neighborhood perception by UPSAI resulted in a rural estimate similar to the OMB classification. The largest HUD-assisted rural population was estimated by the HRSA classification, with 1.35 million people. In general, the percentage of rural population among them fluctuated between 5 percent by the Census Bureau and approximately 15 percent by HRSA. This finding further demonstrates the difference between the location and characteristics of the general U.S. rural population and those assisted by the HUD programs in rural areas. A common estimation is that applying the Census Bureau definition would result in a larger rural population than using the nonmetro OMB classification (Long, Delamater, and Holmes, 2021; Ricketts, Johnson-Webb, and Taylor, 1998). Due to various eligibility criteria and specific locations of public housing and housing projects even without the rurality component, however, the percentage of HUD-assisted individuals residing in the Census Bureau rural area was less than one-half of the assisted population in nonmetro counties.

[5] The author communicated with one of the coauthors of UPSAI on how to best attempt this task; however, the resulting recategorization reflects only the author's perception.

Approximately 75 percent of the HUD-assisted population in OMB nonmetro counties resides in urban areas defined by the Census Bureau, especially on the borders of UAs or UCs.

Exhibit 2

Number of HUD-Assisted Individuals in Rural America by Varying Rural Classifications



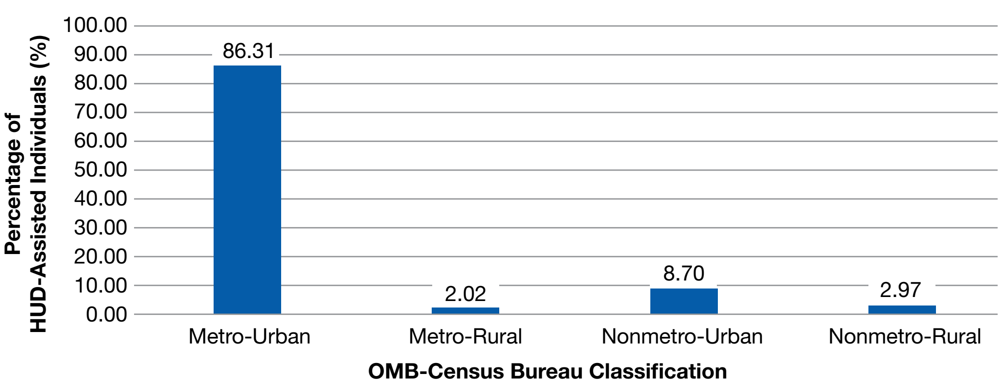
HRSA = Health Resources and Services Administration. OMB = Office of Management and Budget. RUCA = rural-urban commuting area. UPSAI = Urbanization Perceptions Small Area Index.

Source: December 2019 extract standardized across two HUD administrative databases—PIC and TRACS

Exhibit 3 illustrates the cross-tabulation of HUD-assisted individuals using an OMB-Census Bureau classification matrix. Whereas the overwhelming majority of the HUD-assisted population (86.31 percent) resided in both metro (OMB) and urban (Census Bureau) areas, only 2.97 percent of the total assisted individuals resided in nonmetro or rural areas. More than 10 percent of the HUD-assisted population could be considered living in either “rural counties” in urban areas or rural areas in “urban counties” by the Census and OMB classifications.

Exhibit 3

Comparison of Census Bureau (Urban-Rural) and Office of Management and Budget (Metro-Nonmetro) Classifications



OMB = Office of Management and Budget.

Source: December 2019 extract standardized across two HUD administrative databases—PIC and TRACS

Exhibit 4 describes the percentage of overlapping HUD-assisted population among all rural classifications. If OMB classification is used to estimate the rural population (N=1,069,005), then only about 25.45 percent would be considered living in rural areas, by the Census Bureau definition, whereas almost 100 percent of that population is identified by RUCA1 and HRSA definitions. The large overlap with RUCA1 and HRSA makes sense because both are largely based on OMB definitions of metropolitan areas. On the other hand, if the rural population is defined by RUCA1 (N=1,241,434) or HRSA (N=1,345,526), then only about 80 percent of the HUD-assisted rural population can be accounted for by the OMB definition. Because those classifications encompass more metro census tracts as rural than OMB does, almost 100-percent coverage of OMB nonmetro areas by RUCA1 and HRSA seems reasonable.

Exhibit 4

Total HUD-Assisted Rural Population and Overlapping Percentages Among Different Classifications

Classification	HUD-Assisted Population in Rural Areas	Total HUD-Assisted	% Total Assisted Population	% Census	% OMB	% RUCA1	% RUCA2	% HRSA	% UPSAI
Census	456,951	9,162,512	4.99	100	59.53	60.37	70.62	73.25	86.02
OMB	1,069,005	9,162,512	11.67	25.45	100	94.63	24.25	99.91	49.23
RUCA1	1,241,434	9,162,512	13.55	22.22	81.48	100	18.94	99.81	47.46
RUCA2	535,621	9,162,512	5.85	60.24	48.39	56.10	100	62.62	78.62
HRSA	1,345,526	9,162,512	14.69	24.88	79.38	92.08	24.93	100	50.03
UPSAI	1,094,467	9,162,512	11.95	35.91	48.09	53.83	38.48	61.50	100

Census = Census Bureau. HRSA = Health Resources and Services Administration. OMB = Office of Management and Budget. RUCA = rural-urban commuting area. UPSAI = Urbanization Perceptions Small Area Index.

Source: December 2019 extract standardized across two HUD administrative databases—PIC and TRACS

The percentage of HUD-assisted individuals in rural areas by the Census Bureau definition had only one close match in the percentage of HUD-assisted individuals: Census Bureau at 4.99 percent and RUCA2 at 5.85 percent of the total HUD-assisted population, respectively. The cross-tabulation between the rural population by the Census Bureau definition and by the RUCA2 classification resulted in more than 60 percent of the HUD-assisted rural population by RUCA2 overlapping with the Census Bureau rural definition, the highest overlap with the Census Bureau. That finding seemed reasonable because RUCA2 rural areas were delineated from RUCA codes by eliminating urban core areas with primary commuting within the area, similar to the rural areas based on the Census Bureau urbanized areas and urban clusters.

On the other hand, exhibit 5 illustrates the consistency in urban agreement among the urban-rural classification systems. Rural population by each classification can be explained by another classification for approximately 90 percent or more of the HUD-assisted urban population. For instance, HUD-assisted individuals residing in nonmetro counties, by OMB definition, can also be accounted for as urban population by the Census Bureau (97.72 percent), RUCA1 (97.16 percent), RUCA2 (96.58 percent), HRSA (96.57 percent), and UPSAI (92.98 percent).

Exhibit 5

Total HUD-Assisted Urban Population and Overlapping Percentages Among Different Classifications

Classification	HUD-Assisted Population in Urban Areas	% Total Assisted Population	% Census	% OMB	% RUCA1	% RUCA2	% HRSA	% UPSAI
Census	8,705,561	95.01	100	90.85	88.91	97.55	88.39	91.94
OMB	8,093,507	88.33	97.72	100	97.16	96.58	96.57	92.98
RUCA1	7,921,078	86.45	97.71	99.27	100	96.21	98.66	93.62
RUCA2	8,626,891	94.15	98.44	90.61	88.34	100	88.29	92.19
HRSA	7,816,986	85.31	98.44	99.99	99.97	97.44	100	94.61
UPSAI	8,068,045	88.05	99.21	93.27	91.92	98.58	91.67	100

Census = Census Bureau. HRSA = Health Resources and Services Administration. OMB = Office of Management and Budget. RUCA = rural-urban commuting area. UPSAI = Urbanization Perceptions Small Area Index.

Source: December 2019 extract standardized across two HUD administrative databases—PIC and TRACS

Exhibit 6 presents the demographic and economic characteristics of HUD-assisted rural populations. In general, although the total number of HUD-assisted populations differed significantly by the six rural classifications used in the analysis, demographic characteristics on average appeared consistent with each other. The majority of HUD-assisted individuals was female by all rural classifications at approximately 63 percent. Approximately 20 percent of the HUD-assisted population in rural areas was senior (62 or older). Senior individuals with a disability ranged from 43.5 percent to 44.8 percent (only about a 1.3 percent difference) of the total senior population. Non-Hispanic White, Black, and Hispanic rural populations showed more variability. The percentage of non-Hispanic Whites ranged from 51.91 percent to 56.83 percent. The percentage of non-Hispanic Blacks was the highest by UPSAI classification and lowest by RUCA1 definition. The gender of heads of household was predominantly female, from 74.25 percent by OMB classification to 76.43 percent by UPSAI.

Exhibit 6

Characteristics of HUD-Assisted Rural Population by Each Classification (1 of 2)

Characteristics	Census	OMB	RUCA1	RUCA2	HRSA	UPSAI	Min	Max
Gender (%)								
Female (Individuals)	62.83	62.80	62.81	62.91	62.85	63.19	OMB	UPSAI
Female (heads of household)	75.40	74.25	74.39	75.80	74.59	76.43	OMB	UPSAI
Race and Ethnicity (%)								
White, Non-Hispanic	56.83	55.51	54.63	54.63	54.65	51.91	UPSAI	Census
Black, Non-Hispanic	31.25	30.98	30.48	31.25	30.80	33.33	RUCA1	UPSAI
Hispanic	6.77	7.70	9.04	8.86	8.84	8.84	Census	RUCA1
Age Group (% of total)								
Adult (18–61)	43.60	43.78	43.60	43.45	43.60	43.07	UPSAI	OMB
Child (birth–17)	36.84	35.96	36.07	36.71	36.22	37.59	OMB	UPSAI
Senior (62+)	19.56	20.26	20.33	19.84	20.18	19.34	UPSAI	RUCA1

Exhibit 6

Characteristics of HUD-Assisted Rural Population by Each Classification (2 of 2)

Characteristics	Census	OMB	RUCA1	RUCA2	HRSA	UPSAI	Min	Max
With Disability (% of each age group)								
Adult (18–61)	33.22	34.78	34.32	32.60	34.16	32.33	Census	OMB
Child (birth–17)	3.02	2.59	2.71	3.06	2.67	3.17	OMB	UPSAI
Senior (62+)	44.73	43.49	43.50	44.81	43.62	43.97	OMB	RUCA2
Major HUD-Assistance Programs (%)								
HCV	51.02	40.17	41.35	47.33	41.56	50.80	OMB	Census
Project-Based Section 8	21.43	27.28	27.22	22.14	26.98	23.54	Census	OMB
Public Housing	24.68	30.30	29.21	25.51	29.22	22.88	UPSAI	OMB
Majority Income Sources (%)								
SS/SSI-Only Income	59.96	60.22	60.13	59.89	60.09	59.18	UPSAI	OMB
Wage Income	22.28	21.86	21.98	22.67	22.03	23.15	OMB	UPSAI
Welfare Income	3.98	4.16	4.28	4.01	4.23	4.04	Census	RUCA1
Average Household Income ($)	13,888	13,410	13,615	14,196	13,600	14,344	OMB	UPSAI

Census = Census Bureau. HCV = housing choice voucher. HRSA = Health Resources and Services Administration. Max = maximum. Min = minimum. OMB = Office of Management and Budget. RUCA = rural-urban commuting area. SS = Social Security. SSI = Supplemental Security Income. UPSAI = Urbanization Perceptions Small Area Index.

Source: December 2019 extract standardized across two HUD administrative databases—PIC and TRACS

On the other hand, the findings reveal substantial variety in economic characteristics among different rural definitions. Average household income differed by approximately $1,000 between UPSAI ($14,344) and OMB ($13,410) definitions, reflected by the largest number of HUD-assisted households by UPSAI definition reporting wages as the majority of their income source (23.15 percent). Approximately one-half of rural households participated in the HCV program by the Census UPSAI classifications versus only 40.17 percent among the rural population defined by OMB. Also, Project-Based Section 8 and public housing participation were highest among OMB-defined rural households.

Discussion and Conclusion

Because many classifications of rurality exist in the United States, choosing one definition over another could be difficult without practical considerations for degrees of rurality. Even in the future, having one all-purpose definition for rural areas is not likely because rural is a subjective term with varying points of view. Further complications could arise when two foundational rural classification systems, by the Census Bureau and OMB, expand their definitions of rural and nonmetro areas, respectively, to include areas with larger population size and higher socioeconomic characteristics and with current proposals and new standards. Expanding those definitions could have significant effects on rural infrastructure rebuilding and social, economic, and racial equity, resulting in new resource allocation in rural areas.

In this article, the author selected six rural classifications: three dichotomous (Census Bureau, OMB, and HRSA), one trichotomous (UPSAI), and two continuous (RUCA1 and RUCA2).

Significant subjective consideration by the author went into reclassifying RUCA and UPSAI definitions to fit the rural-urban categories. Depending on analytical purposes, reclassifying a continuum of rurality could result in vastly different magnitudes of rural-assisted population. Because the RUCA2 classification delineates RUCA codes in a similar urban-rural dichotomy as the Census Bureau classification, those two definitions showed a close relationship in terms of the demographic and economic characteristics and the total number of HUD-assisted population in rural areas. On the other hand, RUCA1 and HRSA definitions shared a lot of commonalities with the OMB definition and resulted in a HUD-assisted rural population with similar characteristics. Overlapping percentages of HUD-assisted individuals among the definitions varied drastically in rural areas (between 22.22 and 99.91 percent), whereas in urban areas, the overlap of percentages for all the definitions was close to or much more than 90 percent. Because the base population in urban areas is large, small changes in rural population due to different definitions probably did not make much difference. Although OMB and UPSAI classifications produced a comparable size of HUD-assisted rural individuals, with almost 50-percent overlap with each other, and illustrated similar demographic profiles, the economic characteristics of those two populations were almost on the opposite end among the six rural classifications. The differences in more socioeconomic characteristics of various HUD-assisted rural populations are worth investigating in the future. Regional-level analysis could further provide an insight into how different rural definitions could affect the efficiency of targeted assistance delivery. With changing standards for rural and nonmetro areas by the Census Bureau and OMB, further studies into their impact on the characteristics of the HUD-assisted rural population and resource allocation in rural areas are necessary.

Choosing a standard definition of *rural* is directly related to valuable resource allocation in rural communities and has a significant impact on the well-being of rural populations. That definition would affect not only the size and location of the rural population but also how setting up funding eligibility criteria and evaluation studies should be conducted. Careful consideration must take place for the appropriate purposing and geographical level of resource distribution.

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Land Value Capture Across the Globe

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About This Report and the Global Compendium of Land Value Capture Policies

Many countries use land value capture (LVC) policies to some degree, but the instruments, methods, and results differ greatly. The implementation of LVC depends on different historical traditions, the condition of land markets, institutional capacity and experience, and constitutional and legal frameworks. For example, the history of active land policy in the Netherlands is closely linked to considerable public land holdings and municipalities' capacity for large-scale land management (van Oosten, Witte, and Hartmann, 2018). Latin America's long tradition of utilizing infrastructure levies and developer obligations (contribución de valorización and contribución por mejoras) can be partly attributed to historical influences of Spanish law (Henao González, 2005). Land readjustment developed in Japan and Korea after World War II, a period of rapid urbanization marked by increased demand for serviced urban land (OECD, 2022).

Previous case studies on land value capture are mostly limited to developed economies. They document a wide range of approaches to LVC, but they lack systematic, comparable information about the instruments that countries use or the enabling conditions at national and regional levels that can guide local governments. Also, no uniform set of basic terms and names of LVC instruments exists. These barriers present challenges for policymakers in embracing the more frequent and robust use of LVC to manage urban development, mitigate social and spatial inequalities, and advance other goals.

To fill these gaps in knowledge, the Organisation for Economic Co-operation and Development (OECD) and the Lincoln Institute of Land Policy developed the Global Compendium of Land Value Capture Policies, an ambitious undertaking to understand the full landscape of LVC instruments, how they are configured and deployed, and their enabling conditions across the globe in OECD and non-OECD countries. The Compendium features an overview of the LVC approaches in 60 countries, the governance and legal frameworks in which they are embedded, and enabling factors and barriers for their further development. It highlights the differences and similarities among countries, including ones with a mature LVC practice and others where LVC is nascent or undeveloped.

The Compendium allows local and national governments to learn from each other and to understand and apply good practices in different contexts. It can help researchers and policymakers recognize what it would take to unleash the full potential of LVC and can help governments develop the capacity to implement LVC and to understand the opportunities, tradeoffs, and potential pitfalls. Ultimately, it can help policymakers deploy fiscal and planning tools that provide the resources needed for sustainable urban development.

To learn more, read or download the Compendium at https://doi.org/10.1787/4f9559ee-en.

Excerpt begins here.

Introduction

By mid-century, two thirds of the world population will live in urban centres (OECD/European Commission, 2020[1]), driving intense demand for land equipped with infrastructure. This pressing demand for serviced land is strong especially in the urban periphery. At the same time, cities will need to become climate neutral and sharply reduce other environmental footprints, such as from raw materials use. It requires different and more upfront infrastructure investment, including in public transport, sustainable water supplies, renewable energy, and green open space, among others. It also requires better urban planning to make jobs and facilities in cities accessible with low energy input and zero emissions. The land value capture instruments discussed in this article can contribute to meeting these challenges.

The altering of land use or provision of public services by governments often triggers significant increases in the value of land. Making even some of this additional value available for public investment can significantly help make cities more liveable and sustainable. This is because land is one of the most valuable forms of capital. In eight OECD countries, land makes up approximately 40% of the total capital stock. For the entire OECD, this amounts to USD $152 trillion (OECD, 2017[2]).

While local governments increase land value with public investment and changes in land use regulation, they often grapple with fiscal shortfalls holding back efforts to finance and manage urban development. Traditional fiscal policies largely ignore the fact that the cost of providing urban infrastructure is public, but some of the economic benefits, notably those that materialise in higher prices of land are private, meaning that landowners typically reap unearned wealth (Smolka, 2019[3]). A common example is when rural land is converted to residential or commercial uses.

Policymakers need to think creatively about policy instruments to mobilise the resources to pay for needed investment. Land value capture (LVC), also known as land value recovery, is one method that enables governments to recover and reinvest land value increases that result from public decisions. By tapping into the windfall profits public investment and urban planning generates in land ownership, it may also avoid the distortions that taxation imposes on economic incentives. In this way, it may help direct efforts away from rent-seeking behaviour, for example to acquire land for the mere purpose of realising value gains, towards gainful economic activity.

The growing appeal of LVC also includes its potential to put fiscal decentralization into practice. It allows local governments to raise local funds for cities and communities' urban planning and infrastructure needs (Smolka, 2019[3]).

The principles of LVC: How does it work?

LVC is based on the simple premise that public action should generate public benefits. It refers to policies that allow public authorities to recover increases in land values which result from government actions, including the development of land, infrastructure and service deployment, and the alteration of land use regulations (OECD, 2017[2]). This recovered land value serves to fund urban infrastructure and public services.

LVC constitutes three basic steps. First, there is a value creation stage. This is when the government or public administration takes some action on or adjacent to private land, that results in increased land value. This action may be an investment or a change in administrative or regulatory statutes conditioning the use of land. Second, there is the value recovery stage. This is when the full or partial value increase is recovered by the public. Finally, there is the value distribution stage. This is when the recovered land value is reinvested in public benefits.

Hence LVC includes the following elements:

- It refers exclusively to increments in the value of the land.
- It requires a definition of how public action generates land value gains, so they can be recovered.
- Land value increments derived from such public action need to be mobilised by creating LVC instruments. These are commonly fees or in-kind contributions, among others (Smolka, 2013[4]).

From an equity perspective, LVC policies can distribute both the costs and benefits of urbanization and land development, because value capture allows a community as a whole to reap the benefits of development more fully. If land value increments due to public action are not recovered, those increments will remain with private property owners.

Successful LVC requires overcoming a number of challenges, as with any other policy tools. These include building an adequate legal framework and developing administrative and technical capacity to assess land value gains from public actions. Additionally, there can be challenges to secure support from stakeholders. For example, there may be disagreement about how contributions to LVC should be distributed.

While LVC can mobilise additional resources sustainable and more equitable urban development requires, LVC also needs to be implemented in a way that serves this purpose. Land value gains can also result from developing land in an unequitable, unsustainable way. If it is not linked to good planning practices and consistent enforcement of land use regulations, LVC can lead to overdevelopment and increased built-up area, resulting in adverse environmental impacts. As LVC is highly dependent on changes in land values, it can also result in unstable and cyclical fiscal revenues during boom-bust cycles in macroeconomic markets and construction activity (Kim and Dougherty, 2020[5]). Equity benefits will also depend on how the resources mobilised by LVC are used.

The OECD-Lincoln taxonomy of LVC instruments

Providing common definitions for the fiscal or regulatory instruments that comprise LVC is difficult, especially at a global scale, because these instruments are in many cases tightly integrated with broader legislative frameworks, planning practices and property rights that are unique to countries or regions. They are also diverse in scope. They include instruments that levy taxes or fees, in-kind contributions in the form of land or infrastructure, and government practices for managing land and its development.

The 'OECD-Lincoln taxonomy' of instruments developed for the Global Compendium of Land Value Capture Policies stems from extensive debate between the OECD, the Lincoln Institute and leading academics in the field. This taxonomy allows meaningful cross-country comparisons, cutting through the heterogeneous definitions and uses of instruments across the globe. The taxonomy recognises how similar instruments are referred to differently across countries, for example how 'betterment levies' in Colombia are similar in scope to 'special assessments' in the United States. It also minimises confusion by identifying a common set of underlying characteristics for each instrument, thus recognising how, for example, 'infrastructure levies' in Israel and Poland are in fact 'developer obligations' in other countries.

Reflecting the practical difficulties in defining the scope of LVC instruments, the OECD-Lincoln taxonomy is not exhaustive. Firstly, the taxonomy does not include land and property taxes. This is not to say that such taxes do not function as LVC instruments. With the right tax structures, they can indeed effectively recover the value increments triggered by public interventions. However, in practice, it is difficult to delineate and define the role of land taxes as a separate LVC instrument, as they are typically used in a more general fiscal context. This is especially the case as these taxes are usually levied in a uniform manner without distinguishing property owners that are affected by public interventions. Similarly, other tools such as joint ventures, public-private partnerships, or tax increment finance are not included in the taxonomy or the Compendium due to difficulties in delineating their role in capturing value increments.

The OECD-Lincoln taxonomy of LVC instruments is presented next. For each instrument, the taxonomy provides a name, definition, and short description that outlines the defining characteristics of the instrument in question.

Infrastructure levy

> *An infrastructure levy is a tax or fee levied on landowners possessing land that has gained in value due to infrastructure investment initiated by the government.*

With an infrastructure levy, landowners pay a tax or fee for public infrastructure from which they specifically benefit, for example nearby public roads, transport, utilities and parks. The decision to build infrastructure is generally initiated by the government, and is not a consequence of private development interests. The government identifies the catchment area in which landowners are deemed to benefit from public works and pay the levy. The amount of the levy should be based on the amount of land value benefit obtained and can be either a one-time payment or payable over a longer period. Other common terms for the infrastructure levy include betterment contributions, betterment levies or special assessments.

Developer obligations

> *A developer obligation is a cash or in-kind payment designed to defray the costs of new or additional public infrastructure and services private development requires.*

Developer obligations mainly apply when developers seek development approval or special permissions. The obligations can consist of cash or in-kind contributions. In some countries, developers are required to build affordable housing in exchange for approval. This practice, called inclusionary zoning, can be viewed as a form of developer obligation. Unlike the infrastructure levy, developer obligations are triggered by the initiative of private developers and land owners. The obligations can be either negotiated between the government and developers, or calculated using a fixed formula. Common developer obligations include impact fees, negotiated exactions, or development charges.

Charges for development rights

> *Charges for development rights are cash or in-kind contributions payable in exchange for development rights or additional development potential above a set baseline.*

Charges for development rights may be levied to build at a higher density beyond an established baseline that is defined by a jurisdictional ordinance or regulation. Thus, they require clear, predefined land-use and zoning regulations that set baseline and maximum densities. Developers may also be charged for development rights when governments alter zoning or relax density regulations. In some cases, limited development rights, for example in protected environmental areas, can be transferred to a different plot better suited to higher density development. Usually, the types and amounts of cash or in-kind charges are defined in advance in ordinances or local regulations. Related terms include sale of development rights, sale of air rights, and transfer of building rights.

Land readjustment

> *Land readjustment is the practice of pooling fragmented land parcels for joint development, with owners transferring a portion of their land for public use to capture value increments and cover development costs.*

Land readjustment is where privately-owned, contiguous plots of land are pooled and developed jointly. It is often accompanied by zoning changes or relaxed density regulations so that newly developed land becomes more valuable. In turn, landowners provide a share of their plots for public infrastructure and services, such as public roads, utilities and parks. Landowners are returned a smaller plot of land that is nonetheless more valuable due to the improvements made. Land readjustment can be initiated by local governments or private landowners. The instrument is referred to as land pooling in some countries.

Strategic land management

> *Strategic land management is the practice of governments actively taking part in buying, developing, selling and leasing land to advance public needs and recoup value increments borne through public action.*

With strategic land management, governments buy land or use existing land holdings to extract values from them, which can in turn be used to fund public infrastructure and services. If governments acquire land at predevelopment prices, they can fully capture increases in land value that are due to public development or regulatory changes. Governments can recover land value gains with the sale or lease of rezoned and developed plots that are greater in value. Similarly, governments can lease usage rights, capturing value increments through higher rents.

Box 1

Examples of LVC instrument use in practice

Infrastructure levy (Colombia)

The legal basis for the infrastructure levy (contribución de valorización) in Colombia has a long history, dating back to 1921. It applies to public roads, public transport, public utilities and green space, among others. It has been widely used in large and intermediate cities to finance road infrastructure.

The total levy usually amounts to the estimated total cost of public works. In some cases, the levy is proportional to the land value increment, which is often preferred by landowners. Recovery of up to 30% of administrative costs is also allowed by law, although in practice local governments usually charge less than 10%. Affected landowners are identified based on market-based approaches that estimate the distance within which public works increase land values. Landowners pay the levy according to a fixed formula, based on the distance to the new infrastructure, location, size, quality and property value.

Developer obligations (Germany)

Two types of developer obligations exist in Germany, both which are regulated by the Building Code (Baugesetzbuch). ‘Urban development contracts’ (städtebauliche Verträge) cover a wide range of costs generated by private developments, and are always applicable. They are based on formulas that consider the size, type and value of land, or based on negotiations. Charges usually cover a significant share of the public costs. They can be paid through affordable housing, for example in Frankfurt where up to 30% of housing units are required to be affordable rental units. Local governments can also charge ‘development contributions’ (Erschließungsbeiträge) in addition to städtebauliche Verträge if costs associated with utilities, and road construction in the immediate vicinity of private development, if not already covered by the städtebauliche Verträge. These contributions can amount to 90% of public costs.

Charges for development rights (Brazil)

Developers pay charges for development rights for zoning changes (density and use) and for higher density above a baseline determined by local plans and ordinances. Such charges are common in large capital cities such as São Paulo, where the real estate market is dynamic and the Floor Area Ratio (FAR) is low, either historically or through legal reforms. The charge is calculated as a proportion of the extra FAR multiplied by average land price per square meter in some cities, while others such as São Paulo and Curitiba determine charges through an auction market. Development rights can be transferred within the city or a specific zone. Local governments spend collected revenues throughout the city, and some cities have created urban development funds through which revenues are invested.

Land readjustment (Japan)

Land readjustment has been used since the late 19th century, and was formalized in 1954 with the Land Readjustment Act. It is used for urban expansion, urban development or renewal, disaster prevention and reconstruction. An average of 870 land readjustment projects are conducted yearly. Land readjustment projects can be initiated by governments, special public bodies, private entities, and land owners and leaseholders. Land readjustment first needs approval from prefectures, similar to urban planning projects, as well as the consent of at least two-thirds of involved landowners and leaseholders. Typically, 30-40% of readjusted plots are reserved for public improvements including infrastructure and utilities. Newly readjusted areas also typically include publicly owned plots for sale, which are used to recover development costs.

Strategic land management (Netherlands)

Strategic land management (called Active Municipal Land Policy) plays a crucial role in spatial planning, housing policy, and land value capture in the Netherlands. The instrument is mainly used in the largest cities of Amsterdam, Rotterdam, The Hague and Utrecht. The legal basis is defined in “Besluit Begroting en Verantwoording Provincies en Gemeenten” (BBV) and the “Mededingingswet” (Competition Law), which outlines conditions for how municipalities must act as market players in the land market. Typically, local governments acquire vacant, abandoned or unproductive land through debt financing (e.g. bonds), in advance of needs for the purposes of urban development, spatial planning, and capture of capital gains. After rezoning, municipalities service the land through physical preparation and the building of public spaces and infrastructure. Local governments recover initial investments through the sale or lease of the developed plots.

Source: Authors’ elaboration based on OECD-Lincoln LVC survey

Data and survey methodology

The analysis presented in this article is based on unique data from a large-scale questionnaire covering aspects of LVC instruments and their legal and enabling frameworks. The 'OECD-Lincoln LVC survey' was a joint initiative of the OECD and the Lincoln Institute, with significant contributions from Deutsche Gesellschaft für Internationalle Zusammenarbeit (GIZ) GmbH. Country-level data for 60 OECD and non-OECD countries was collected over the course of 2020 and 2021. Box 2 provides further details concerning the survey methodology.

Box 2

The OECD-Lincoln LVC survey

Data collection for the OECD-Lincoln LVC survey began with the OECD developing a comprehensive questionnaire in close collaboration with the Lincoln Institute. The methodology and content of the questionnaire also benefited from consultation with an expert advisory group set up by the OECD and the Lincoln Institute, comprised of leading urban planning, economics and law experts. The questionnaire was first piloted in three countries—Brazil, Japan, and the Netherlands—to identify potential issues, and the final version of the questionnaire was completed online during the course of 2020 and 2021 by a pool of academic experts having substantial expertise of LVC practices in each country. These experts were identified jointly by the OECD and the Lincoln Institute, with special contribution from GIZ. The completed questionnaires were reviewed by the OECD Secretariat, after which revisions were conducted until early 2022.

The questionnaire covered all main aspects of LVC, including the legislative and administrative frameworks, enabling factors and obstacles, along with detailed information concerning the use of individual LVC instruments in a particular country. The questionnaire included over 350 queries. Respondents were given 6 to 8 weeks to complete the questionnaire, with extensions provided upon request. As much as possible, respondents were asked to refer to typical scenarios of LVC use in the country within the last 10 years. Respondents were asked to choose cities, municipalities, or states that are as representative as possible of the entire country, according to individual best judgement.

The main aim of the questionnaire was to collect data comparable across countries on the use of LVC, while also considering each country's nuances and specificities. While it relied mostly on closed-ended questions to obtain comparable, factual information, responders were asked to provide additional information in open-ended format to contextualise the standardised responses. To reduce confusion, the questionnaire also refrained from referring to instruments by name, rather giving detailed descriptions and use-case scenarios to describe the instrument in question.

Table 1 provides a tabulation of the countries studied based on location and income levels: 27 (45%) of countries are located in Europe, followed by 12 (20%) in the Asia-Pacific region, 11 (18%) in the Americas, and 10 (17%) in the Middle East and Africa. 35 (58%) of the countries studied are high-income economies. Notably, data was also collected for 11 (18%) lower-middle income countries, as well as 2 (3%) low-income countries (Ethiopia and Uganda).

Table 1

Countries in the study by continent and income level

	Americas	Asia & Pacific	Europe		Middle East & Africa
High-income	Canada Chile United States	Australia Hong Kong Japan Korea New Zealand Singapore	Austria Belgium Czech Republic Denmark Estonia Finland France Germany Greece Hungary Ireland Italy Latvia	Lithuania Luxembourg Netherlands Norway Poland Portugal Slovak Republic Slovenia Spain Sweden Switzerland United Kingdom	Israel
Upper-middle income	Argentina Brazil Colombia Costa Rica Dominican Republic Ecuador Mexico Peru	China	Turkey		Namibia South Africa
Lower-middle income & Low-income		Bangladesh India Indonesia Pakistan Vietnam	Ukraine		Egypt Ethiopia Ghana Morocco Nigeria Tunisia Uganda

Note: Classification of countries into income groups is based on World Bank country and lending groups for 2022, utilising 2020 GNI per capita calculated using the Atlas method. Low-income countries are those with a GNI per capita of $1,045 or less; lower middle-income countries are those with a GNI per capita between $1,046 and $4,095; upper middle-income economies are those with a GNI per capita between $4,096 and $12,695; high-income economies are those with a GNI per capita of $12,696 or more.

Source: World Bank (2022[9]), World Bank Country and Lending Groups, https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups (accessed on 25 Feb 2022); OECD-Lincoln LVC survey

The enabling environment for Land Value Capture

Implementation of LVC instruments depends on the enabling environment, including the constitutional and legal frameworks along with the administrative system. Legislative frameworks are important for setting the legal basis for LVC, defining procedures and coordinating intergovernmental interests, among others. Administrative systems such as the planning system, land registries, cadastres and land valuation mechanisms are critical to implementing LVC. Differences in these frameworks and systems leads to a wide variation in LVC utilisation across countries. The following sections highlight these observations.

Constitutional and legal frameworks

LVC is closely linked to the principle of social function of property and the principle of unearned income. The former implies that private property rights are limited by an obligation to use property (including land) in ways that benefit society as a whole. The latter implies that no citizen should accumulate wealth that does not result from his or her own effort. The majority of surveyed countries have at least the principle of social function of property embedded in their constitutions, while 12% of countries, mostly in South America and Africa, also embed the principle of unearned income.[1] However, only 21% of countries specifically define LVC in legislation. Incorporating these definitions into law can reduce legal disputes and garner citizen support, two issues commonly stated to be major obstacles in LVC implementation across many countries. For example, the *Organic Law of Spatial Planning, Land Use and Management* of Ecuador establishes LVC as the "equitable distribution of the benefits of public actions, and decisions on the territory and urban development in general", while stating that "society has the right to participate of these benefits under the social function of property". In Spain, Article 47 of the 1978 Constitution states that "the society will participate in the land value gains produced by the urban actions of public entities".

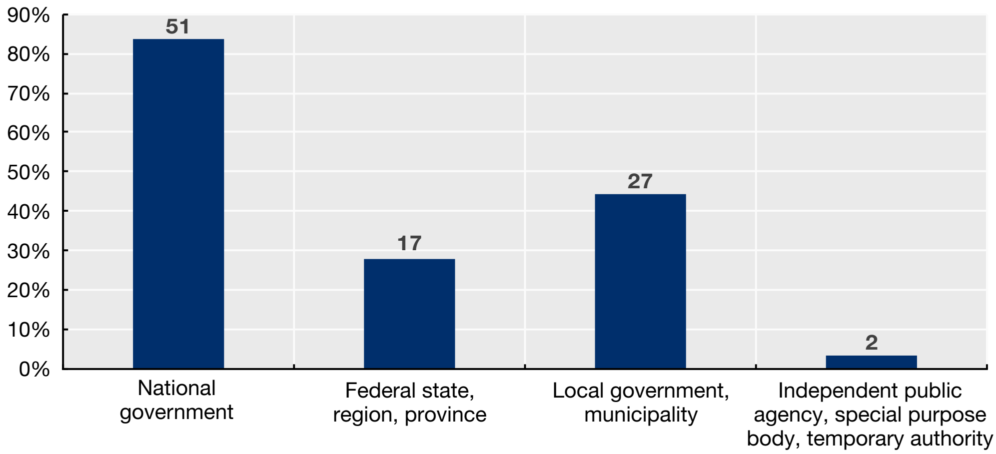
The national government is in charge of creating the framework legislation for LVC in most countries (Figure 1). This is in contrast to the actual implementation of LVC, which is largely the responsibility of subnational actors in most countries. Out of the 51 countries where national governments play a role, 43% do not share legislative responsibilities with subnational governments, while only 35% shared responsibilities with local governments or municipalities. Whether the hierarchy of responsibilities in defining legal frameworks for LVC has an effect on local government initiative and capacity to effectively use LVC is an open area of research. Further understanding of the drivers and motivating factors for local governments in implementing LVC is needed.

Legal frameworks are closely connected with governance traditions of countries. In unitary countries or centralised federal countries, guidelines and a legal basis for LVC provided by national governments could be helpful in implementing LVC more effectively. Conversely, in federal countries where states have strong levels of autonomy, a national legal basis for LVC may not necessarily be useful, or realistic. In the United States, Canada and Australia for example, states are responsible for LVC frameworks and implementation (OECD, 2017[10]). How legal frameworks determine the frequency and effectiveness of LVC implementation differently across a range of government structures is another topic open to research.

[1] Figure 1 of the originally published report has been omitted from this reprinted version. To view the figure, please visit https://www.oecd-ilibrary.org/urban-rural-and-regional-development/global-compendium-of-land-value-capture-policies_4f9559ee-en.

Figure 1

Governments involved in LVC legislation

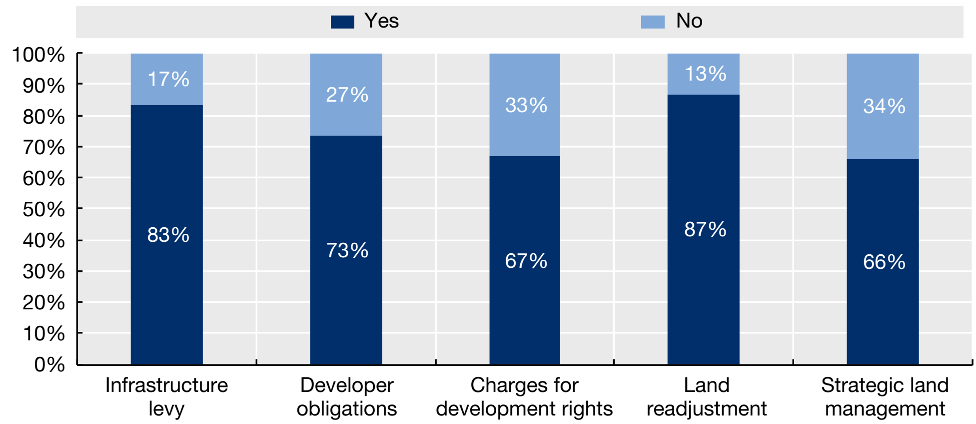


Note: Multiple responses allowed. Labels indicate the number of countries in each category.
Source: Authors' elaboration based on OECD-Lincoln LVC survey

While most countries do not specifically define LVC in national legislation, the majority of surveyed countries do have a legal basis for individual LVC instruments (Figure 2). Over 80% of countries utilising infrastructure levies and land readjustment have a basis for them in law that outlines implementation procedures and criterion for use. The legal basis for charges for development rights and strategic land management is comparatively less widespread, with roughly one-third of surveyed countries indicating no such basis in legislation. For charges for development rights, this may be due to the fact that the instrument, and its use, is comparatively new. Legislation in most countries, when present, has only been in place since the late 1990s. For example, related legislation was only enacted in 2001 in Brazil, a country well-known for the use of Certificates of Additional Construction Potential (known locally as CEPACs, or Certificados de Potencial Adicional de Construção). For strategic land management, many of the activities that constitute LVC are regular government tasks, possibly making specific legislation unnecessary or difficult to enact.

Figure 2

Presence of legal basis for LVC instruments

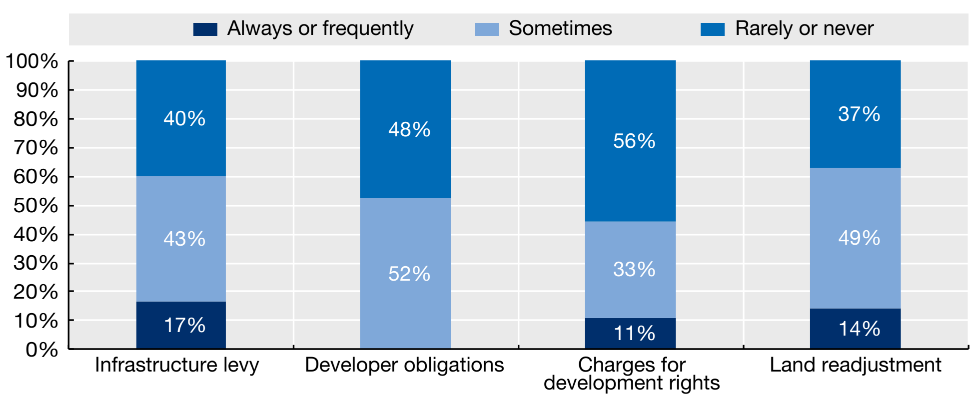


Source: Authors' elaboration based on OECD-Lincoln LVC survey

Legal appeals against the use of LVC instruments are common, although variation exists across instruments (Figure 3). They are most common for the infrastructure levy and land readjustment. Appeals against developer obligations and charges for development rights are comparatively less common. Such patterns likely relate to individual instrument characteristics. The infrastructure levy is commonly charged against the interests of property owners for infrastructure investments that benefit the general public, and not individual owners. Similarly, land readjustment requires that private land owners give up a portion of land for the public good, as a result of government action. Appeals are more likely to arise in such cases, compared to developer obligations and charges for development rights which apply when developers take the initiative to apply for development approval, and not involuntarily through government action.

Figure 3

Frequency of appeals against the use of LVC



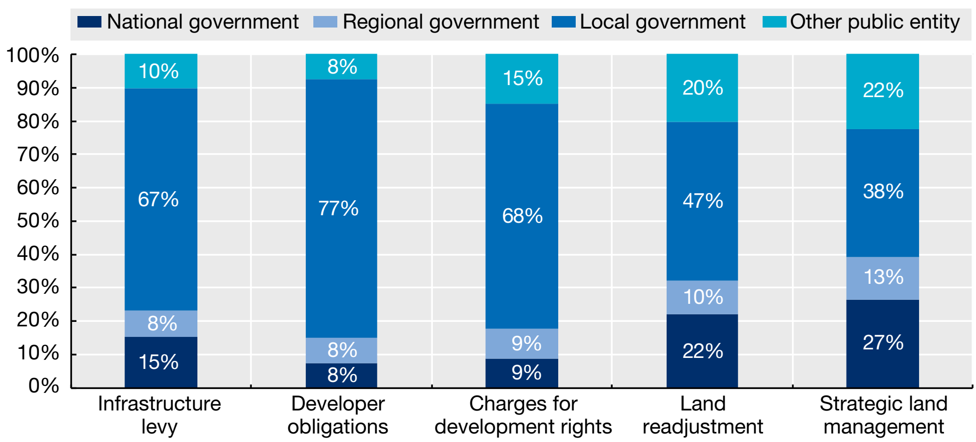
Note: Not applicable for strategic land management.
Source: Authors' elaboration based on OECD-Lincoln LVC survey

Administrative system

The implementation of LVC is mostly the responsibility of local governments (Figure 4). However, some variation exists across instruments. The majority of countries task local governments with the implementation of the infrastructure levy, developer obligations and charges for development rights. Responsibilities for land readjustment and strategic land management, however, tend to be shared with the national government and other public entities, such as government-owned corporations.

Figure 4

Administrative responsibilities for LVC implementation



Note: Administrative responsibilities include levying fees, issuing development approvals, selling development rights, and pooling, rezoning, and managing land, depending on the instrument. Other public entities may include independent public entities, special purpose bodies, publicly owned non-profit organisations, and temporary authorities. Multiple responses allowed.

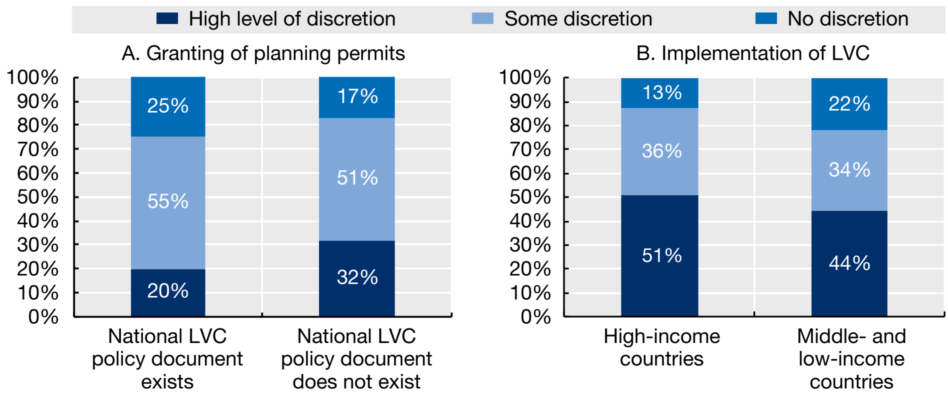
Source: Authors' elaboration based on OECD-Lincoln LVC survey

Local officials have at least some level of discretion in granting planning permits in 49 out of 60 countries surveyed. Countries having national policy documents concerning LVC tended to award a lower level of discretion to local officials (Figure 5, panel A). It is important to note that higher discretion for local officials does not necessarily preclude the need for a LVC policy document at the national level, as such documents may be important in aligning interests and initiatives across government levels while providing the working conditions for LVC implementation. Denmark, Norway, and Egypt are examples of countries that award a high level of discretion to local planners while still maintaining national policy documents.

Middle and low-income countries tend to award a lower level of discretion to local officials for implementing LVC compared to high income countries. For example, local officials in countries such as the Dominican Republic, Nigeria, Peru, and South Africa have no discretion in estimating LVC fees or in reinvesting collected funds. Among other issues, fear of corruption and lack of trust in local governments is a common reason for limiting the discretion awarded to local officials in implementing LVC.

Figure 5

Level of discretion awarded to local officials

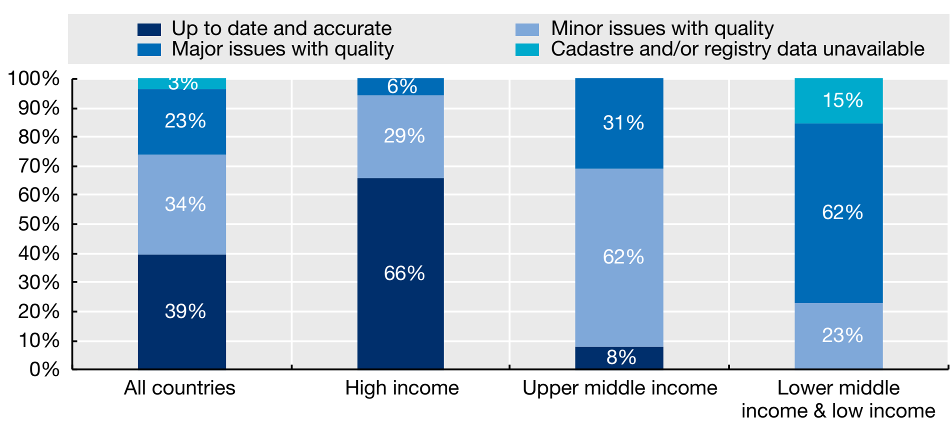


Note: Country income groups determined based on World Bank country and lending groups for 2022. See Table 1 notes for further information. Percentages for panel B are an average over all relevant instruments.
Source: Authors' elaboration based on OECD-Lincoln LVC survey

The survey highlights a gap in quality cadastre or registry data for local governments especially in middle- and low-income countries. This makes it difficult for local governments to properly implement LVC, as accurate data on land is essential for carrying out key administrative tasks. Across all countries, 26% either had no land cadastre or registry data available or had major issues in the quality of this data (Figure 6). The problem is particularly pronounced in lower middle-income and low-income countries, with 10 out of 13 having major issues or no available data altogether. Providing this data to local governments possibly through independent bodies or with help from the central government is needed to boost administrative capacities and properly implement LVC instruments. For higher income countries, the administrative capacity to analyse existing cadastres and registries in implementing LVC is often cited as a common obstacle, rather than availability of the underlying data per se.

Figure 6

Quality of cadastres and land registries

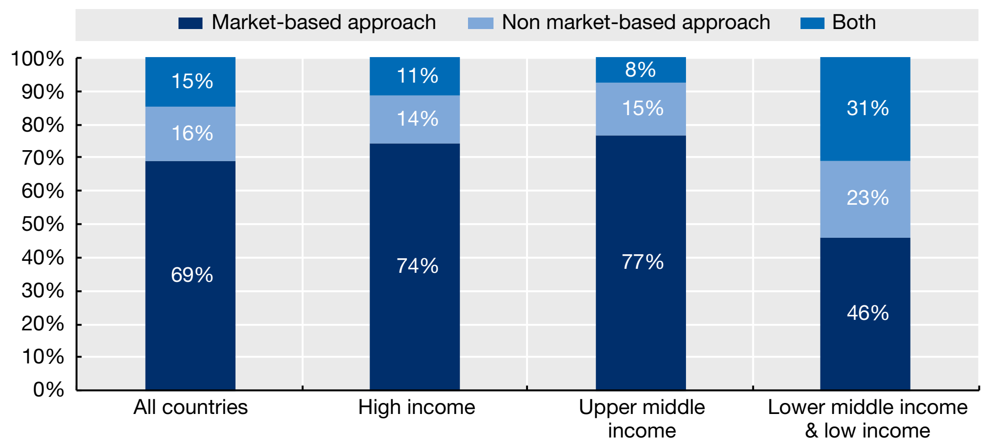


Note: Country income groups determined based on World Bank country and lending groups for 2022. See Table 1 notes for further information.
Source: Authors' elaboration based on OECD-Lincoln LVC survey

The lack of quality cadastres and registry data results in more lower income countries resorting to non market-based approaches for land valuation (Figure 7). Market-based approaches for land valuation are generally preferred due to their accuracy and ability to differentiate plot values at a granular level. Such approaches also better justify the value capture process and can reduce legal conflicts. For lower-income countries, providing cadastre and registry data to local governments together with administrative support measures is necessary to promote effective use of LVC. The cases of Costa Rica, Ghana, India, Indonesia, Nigeria, and Peru among others, highlight in particular the need for such measures.

Figure 7

Methods for land valuation



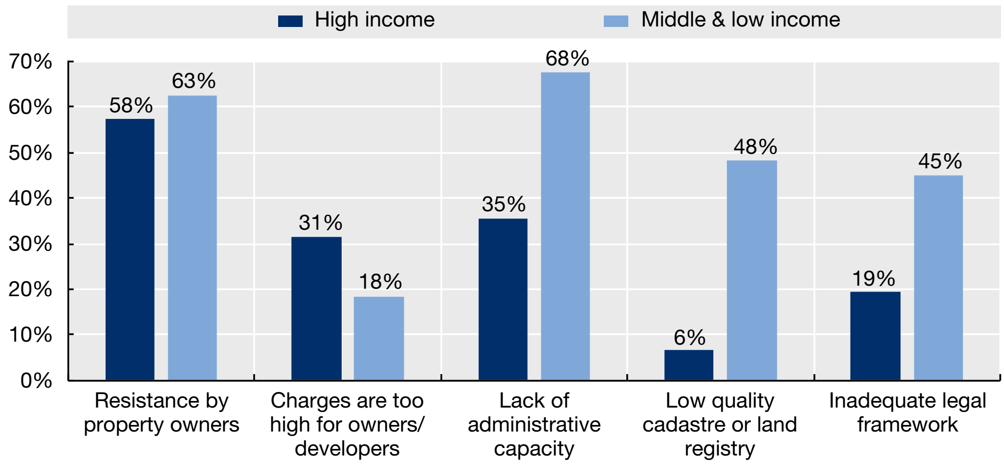
Note: Country income groups determined based on World Bank country and lending groups for 2022. See Table 1 notes for further information.
Source: Authors' elaboration based on OECD-Lincoln LVC survey

Obstacles for LVC implementation

Across all countries, the most common obstacle in LVC implementation is resistance by property owners, followed by lack of administrative capacity (Figure 8). Owners' resistance is a common obstacle for the majority of countries regardless of income levels, while middle- and low-income countries in particular are burdened by a lack of administrative capacity. For high-income countries, the charges or fees that are levied on land owners and developers are often too high, compromising the successful implementation of LVC instruments. For middle- and low-income countries, low quality cadastres and land registries together with inadequate legal frameworks are common obstacles in the successful implementation of LVC. Among other obstacles not shown in Figure 8, by far the most common was political will, stated as a major obstacle in countries regardless of income levels.

Figure 8

Common obstacles for LVC implementation



Note: Country income groups determined based on World Bank country and lending groups for 2022. See Table 1 notes for further information. Percentages are an average over all relevant instruments.

Source: Authors' elaboration based on OECD-Lincoln LVC survey

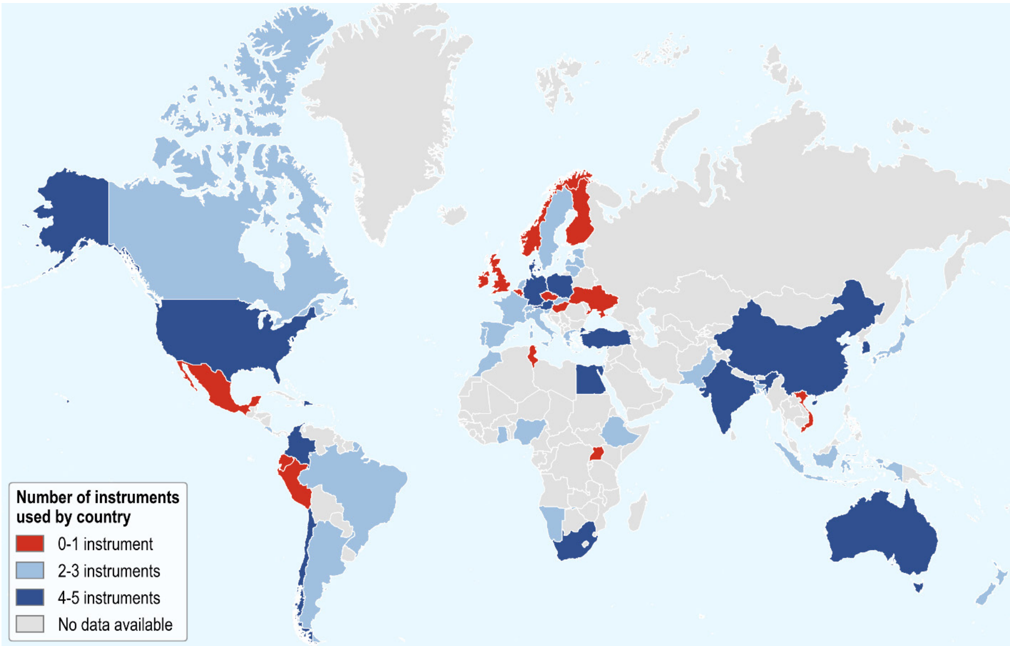
An overview of LVC instrument use across the globe

Figure 9 depicts the number of instruments used by countries studied, while Annex A provides maps of the frequency of use of individual instruments. All countries excluding Uganda use some form of value capture at least on an occasional basis. Developer obligations are the most common instrument, followed by strategic land management (Figure 10). Charges for development rights were least common. European countries tend to rely more on developer obligations and strategic land management, while the use of charges for development rights is relatively rare. Most Middle Eastern, African and Asia-Pacific countries utilise strategic land management. Charges for development rights are common in the Asia-Pacific, while land readjustment in the Americas is particularly rare.

Figure 9

Use of LVC instruments across countries

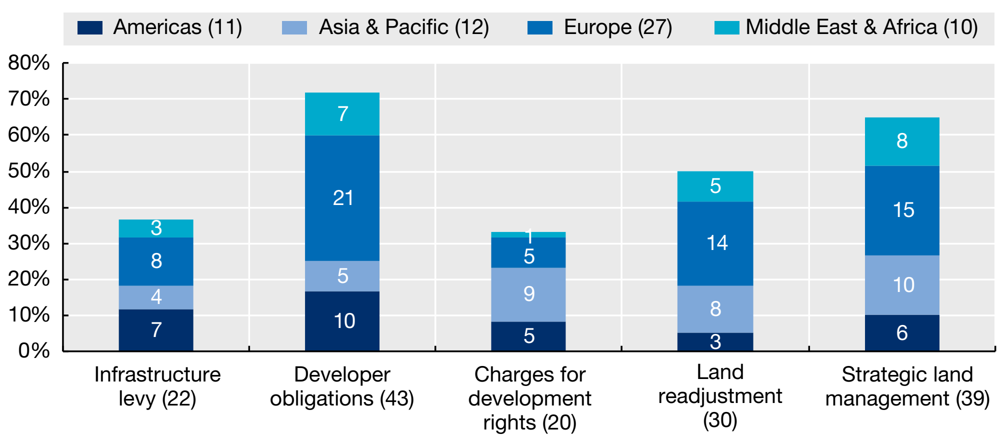
Number of LVC instruments countries use at least on an occasional basis



Note: Instruments that are used only rarely are excluded from counts.
Source: Authors' elaboration based on OECD-Lincoln LVC survey

Figure 10

Frequency of LVC instrument use

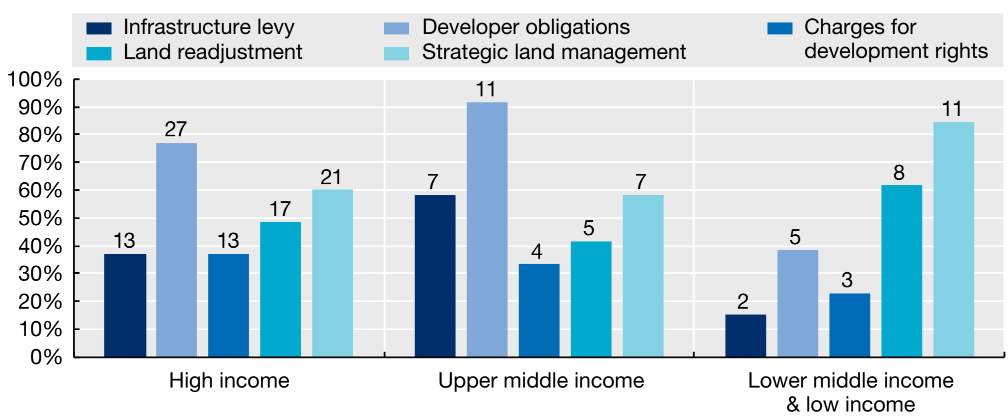


Note: Countries using the instrument only rarely are excluded from counts. Labels indicate the number of countries in each category.
Source: Authors' elaboration based on OECD-Lincoln LVC survey

Low- and lower middle-income countries use an average of 2 LVC instruments at least on an occasional basis, compared to 2.5 for high- and upper middle-income countries. Chile, Egypt and India use all five instruments on a regular basis. Low- and lower middle-income countries rely more on strategic land management and land readjustment compared to high- and upper middle-income countries (Figure 11). This is likely due to the rapid urbanisation occurring in lower-income countries. Urbanisation necessitates the strategic management of land by local and national governments, evident in countries such as China, Egypt, Ethiopia and Vietnam. Land readjustment is also a useful planning tool in the urbanisation process as value increments from converting rural to urban land are high, such as in the cases of China and India. High- and upper middle-income countries use developer obligations much more frequently than countries with lower income levels (e.g., Chile, France, Greece, Israel, Italy, Korea, Netherlands). Possible reasons for such patterns include that developer obligations are generally more administratively demanding, and that expected standards for infrastructure and services are higher in higher-income countries, necessitating a transfer of some of these additional costs from the government to developers. However, basic government services are needed in poor countries as well. With the right governance frameworks, making greater use of developer obligations in poor countries, especially for new developments, could provide additional funding for governments in providing infrastructure and key services. For example, countries such as Egypt and Ghana use developer obligations frequently during approval processes for developments. Nonetheless, issues including corruption, low-quality cadastres and land registries, along with administrative capacity are cited as common obstacles for their effective implementation.

Figure 11

Use of LVC instruments by country income levels



Note: Countries using the instrument only rarely are excluded from counts. Country income groups determined based on World Bank country and lending groups for 2022. See Table 1 notes for further information. Percentages are calculated based on the number of countries in each income group. Labels indicate the number of countries in each category.

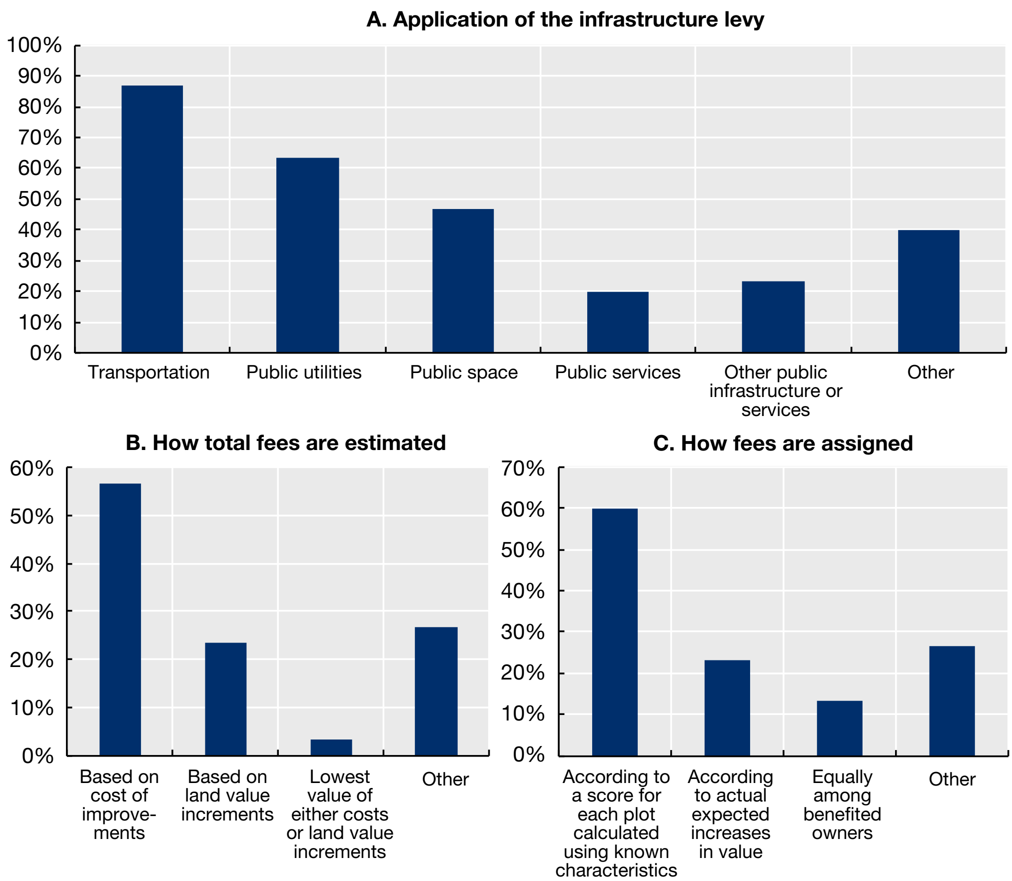
Source: Authors' elaboration based on OECD-Lincoln LVC survey.

Infrastructure levy

The infrastructure levy most often applies to transportation infrastructure (Figure 12, panel A), followed by public utilities and public space. The common use of the infrastructure levy for transport and utilities is related to the fact that their catchment areas are relatively straightforward to define, facilitating the identification of paying owners and minimising the likelihood for disputes. Among other applications, countries use the infrastructure levy for urban management, such as services related to crime, and for sustainability efforts such as soil rehabilitation and noise reduction. In Mexico, the infrastructure levy can be applied theoretically to any public investment.

Figure 12

Implementation of the infrastructure levy



Note: Multiple responses allowed.
Source: Authors' elaboration based on OECD-Lincoln LVC survey

The amount of fees that need to be collected through the infrastructure levy for a particular infrastructure project are usually estimated based on the cost of the improvement (Figure 12, panel B). Only 23% of countries estimate the amount of total fees based on actual land value increments. This is likely because estimating value increments for land is difficult, especially for local governments that often lack administrative capacity and expertise. Additionally, there may be opportunities for localities to make administrative processes more efficient. However, basing fees on the cost of improvements rather than actual value increments risks controversies and disputes with land owners, as fees may not necessarily coincide in proportion to land value gains. Perhaps not by coincidence, appeals against the infrastructure levy are most common out of all instruments (Figure 3).

The fees levied are assigned mostly according to a score based on known characteristics of plots (Figure 12, panel C). These typically include area, zoning, density levels, taxable values, and distance from the improvement. Countries such as Colombia and Spain use a variety of characteristics of plots, while others such as France and the United Kingdom calculate fees based on land area alone. The prevalent use of known characteristics is likely because calculating actual value increments is administratively challenging, while levying fees equally among owners is often controversial.

Developer obligations

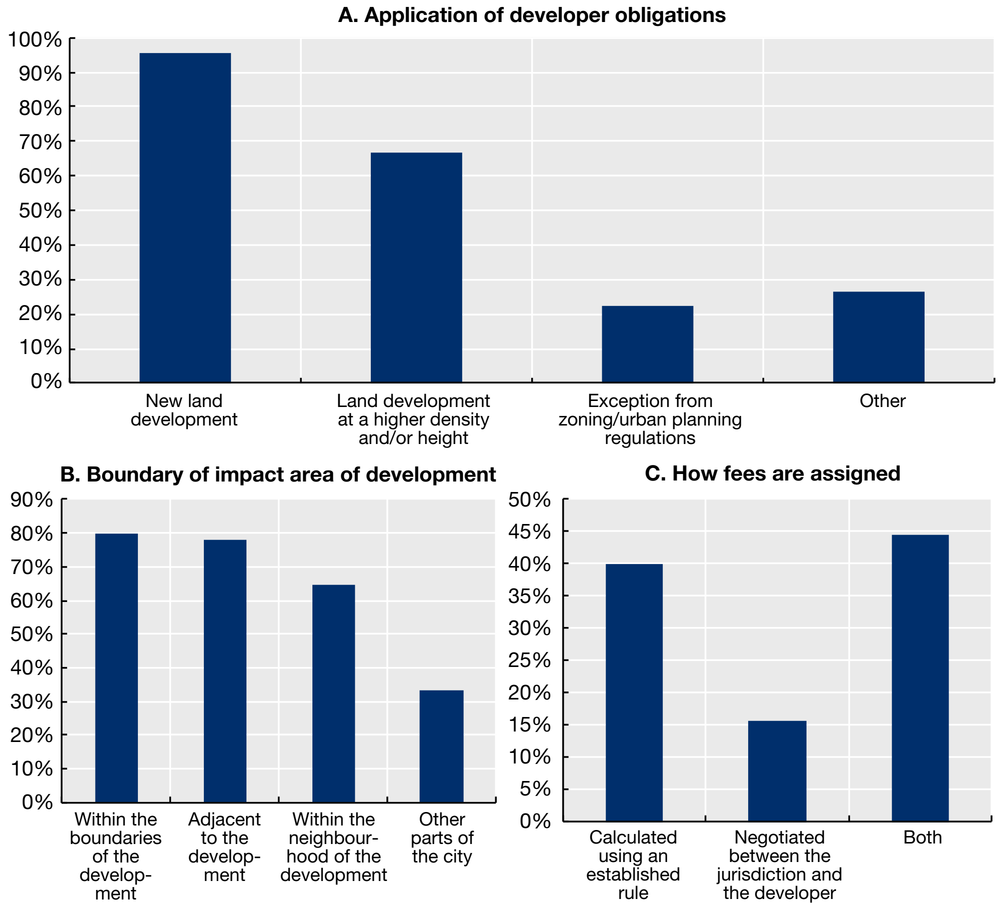
Developer obligations are in essence fees or contributions developers pay in exchange for development approval, which fund or directly provide for public services. Of countries that utilise the instrument, over 90% apply them towards new land development applications, while over 60% of countries apply them when developers file for approval for higher density developments (Figure 13, panel A). The application of developer obligations for exemptions from planning regulations is less common. Among other use cases, Norway and Poland use developer obligations for urban redevelopment, while Finland applies developer obligations when local governments alter land use plans.

Defining the impact area of the development is important for implementing developer obligations, as this area determines where new infrastructure is required. 79% of countries consider the impact area to be within the boundaries of development, and charge fees or mandate contributions for infrastructure within these boundaries (Figure 13, panel B). In countries such as Finland, France, and the Netherlands, the impact area stretches out to other parts of the city, meaning that in principle, fees and contributions can be levied for infrastructure works across the city or jurisdiction.

Developer obligations tend to be assigned more frequently based on established rules, rather than through negotiations between the jurisdiction and the developer alone (Figure 13, panel C). This is likely to reduce legal disputes and streamline the development approval process. However, many countries also use both established rules and negotiations. For example, France uses two different types of developer obligations, the *taxe d'aménagement* and the *contributions d'aménagement*. The former levies a fixed cash charge per square metre, while the latter levies cash or in-kind contributions based on negotiations with developers in designated urban development zones. Local governments increasingly use the rule-based method to streamline procedures and reduce costs.

Figure 13

Implementation of developer obligations



Note: Multiple responses allowed for panels A and B.

Source: Authors' elaboration based on OECD-Lincoln LVC survey

Charges for development rights

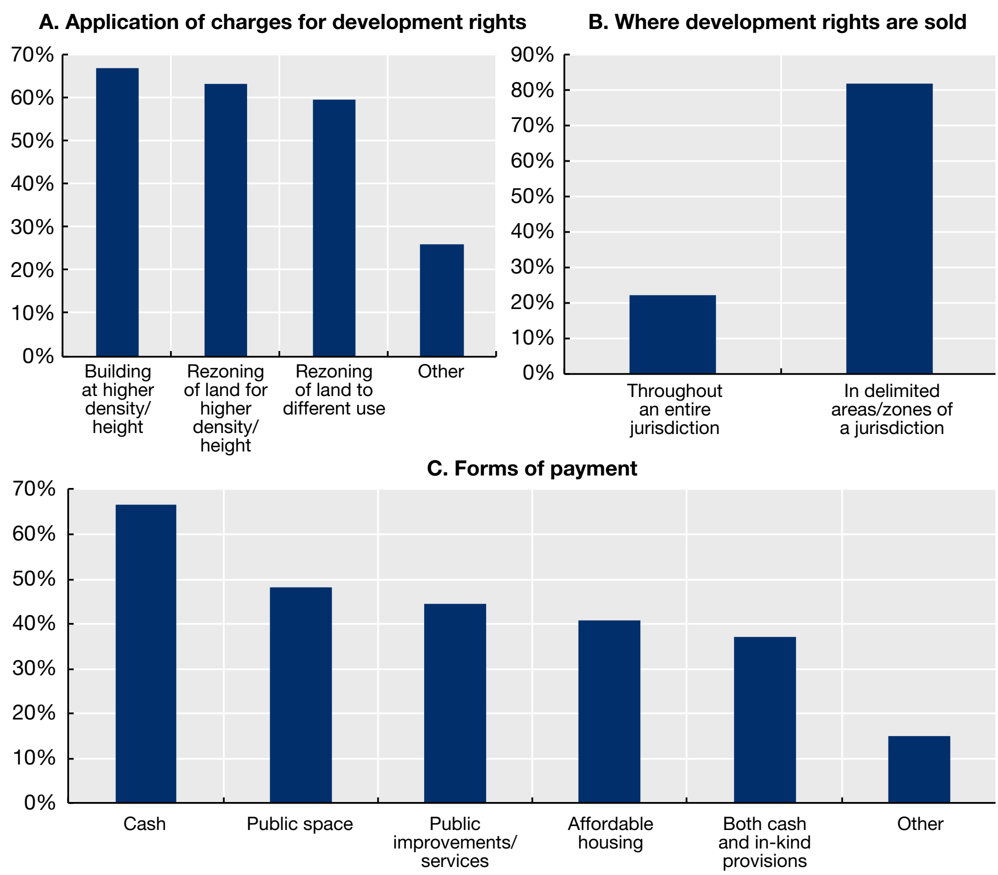
In most countries, developers mainly pay charges for development rights for building at higher density, and when applying for zoning changes that increase permitted densities or alter land use (Figure 14, panel A). In countries such as Brazil, China, and Italy, these charges apply for a broad range of development activity related to building and rezoning. In other countries such as Canada, charges for development rights apply only when development at a higher density actually takes place, and not for zoning changes. Among other use cases, in China and Singapore, charges for development rights are used when renewing land leases.

In the majority of countries, charges for development rights apply to specific zones within a jurisdiction (Figure 14, panel B). Such zones commonly include areas demarked for environmental protection, or historical preservation districts. In the United States for example, Incentive Zoning and Density Bonusing apply to specific areas within jurisdictions determined by ordinances. In countries such as Brazil, development rights are sold throughout the entire jurisdiction, by charging for additional development rights above an established baseline but within the maximum density permitted by local plans.

Charges for development rights can be paid for in a variety of ways (Figure 14, panel C). The majority of payments take the form of cash, followed by in-kind contributions including the provision of public space, infrastructure and services, as well as affordable housing. While still less common, the provision of affordable housing in particular has become increasingly popular. In Korea for example, new national legislation was introduced in 2009 outlining affordable housing requirements for housing development projects in the Seoul Metropolitan Area, and in 2011 for the rest of the country. Under the law, affordable housing units remain affordable for up to 30 years, and benefit households with an income below 70% of the median income of the area.

Figure 14

Implementation of charges for development rights



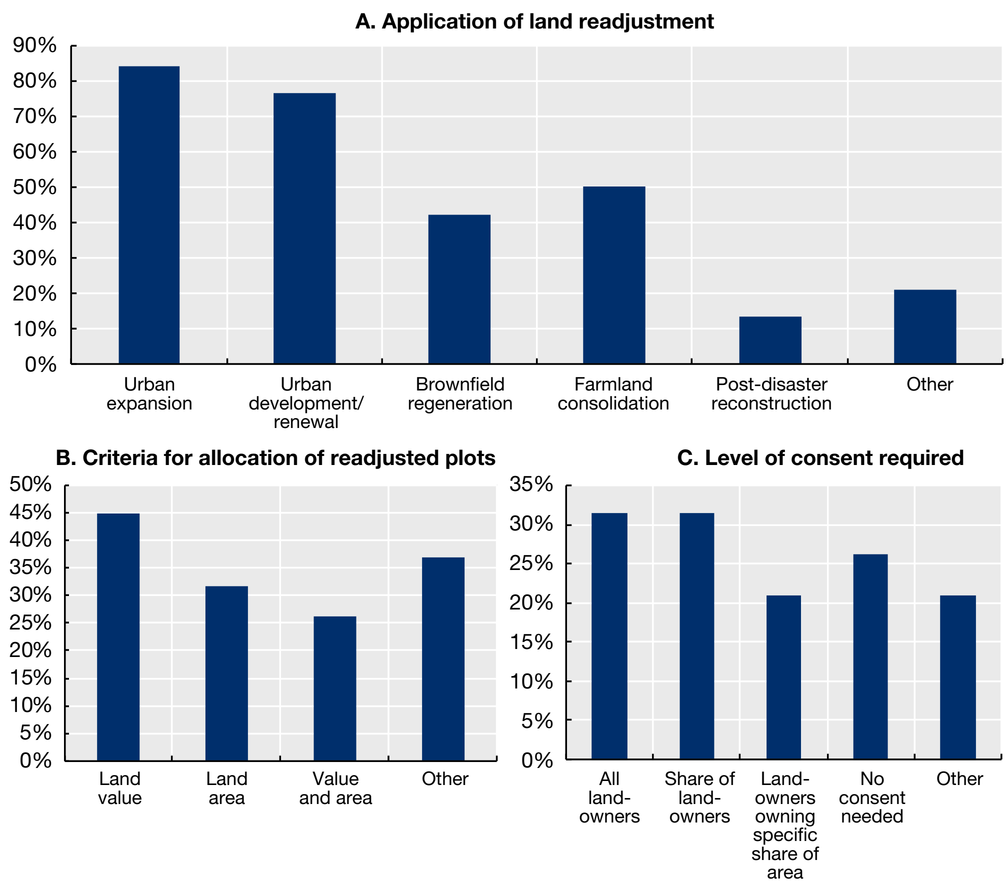
Note: Multiple responses allowed.
Source: Authors' elaboration based on OECD-Lincoln LVC survey

Land readjustment

Land readjustment has traditionally been used extensively in converting from rural to urban land use. Over 80% of countries use land readjustment for this purpose (urban expansion), which is still the most common use case today (Figure 15, panel A). Another common use of land readjustment is for urban developments and renewals, followed by farmland consolidation and brownfield regeneration projects. Countries including India, Italy and Japan also utilise land readjustment for the reconstruction and reservicing of plots affected by natural disasters. Among other uses, land readjustment is also used to consolidate forests (Finland), construct railways (Estonia), and to simplify complex property ownerships in areas where government owned land is interspersed with private plots (Israel).

Figure 15

Implementation of land readjustment



Note: Multiple responses allowed.

Source: Authors' elaboration based on OECD-Lincoln LVC survey

Countries utilise a variety of approaches to reallocate plots that have been readjusted. Most commonly, land is reallocated proportionally based on the value of the original plots (Figure 15, panel B). Other countries such as Indonesia, Italy, and Turkey exclusively use the area of the original plots as the criteria for reallocation, while countries such as Chile and China use a combination of value and area-based criteria. Notably, Israel and Hong Kong apply vertical land readjustment practices, where land owners are reallocated housing units or specific portions of buildings rather than plots of land.

The level of consent required among landowners to commence land readjustment projects also varies significantly across countries (Figure 15, panel C). A roughly equal number of countries require either the consent of all land owners, a certain share of landowners, or no consent whatsoever. When a share of landowners are required to consent, this share is typically two-thirds of all affected owners, although Colombia and Korea only require a simple majority (i.e. 51%). In Austria, land readjustment typically occurs for agricultural areas, where there is no need for property owners' consent. In countries such as Portugal, landowners face expropriation in instances where full consent is not achieved.

Strategic land management

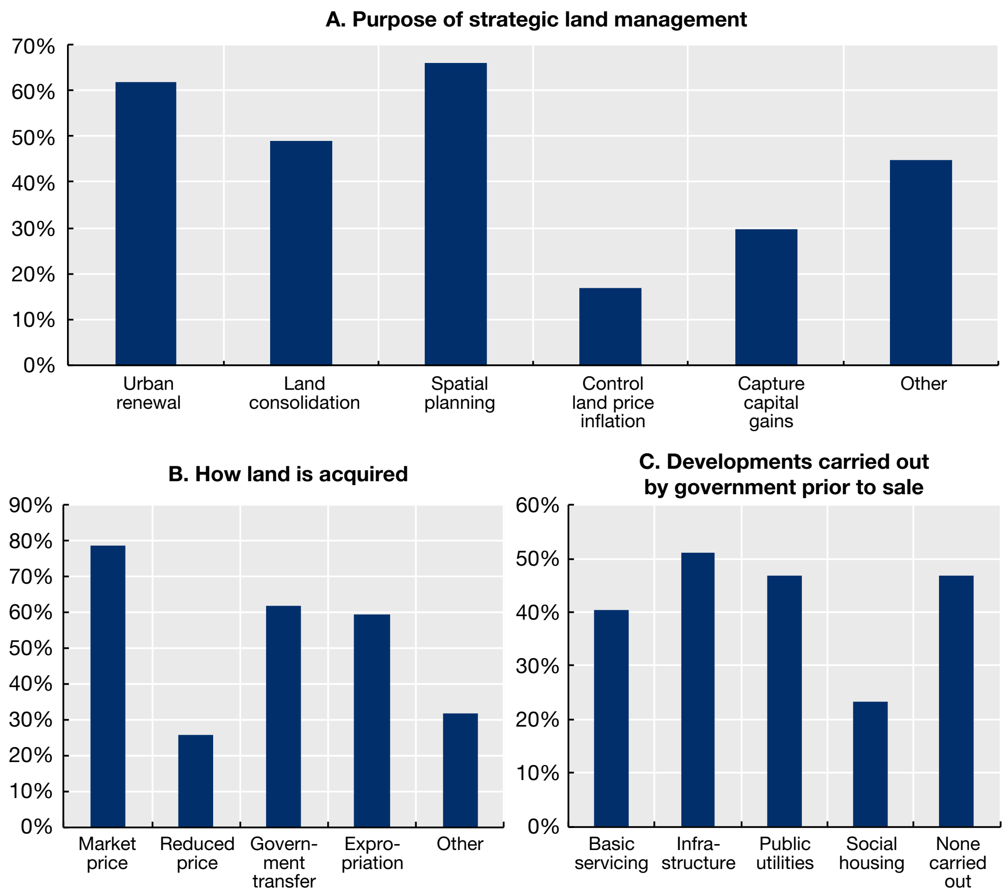
Governments engage in strategic land management mainly to promote coherent spatial development, including for spatial planning, urban renewal, and land consolidation (Figure 16, panel A). In countries such as Singapore and Switzerland, governments also engage in strategic land management to control land price inflation. Among other purposes, strategic land management is often used to provide for social housing in countries such as Australia, Canada, Colombia. Mexico uses the instrument to promote strategic projects related to tourism, while Ethiopia uses it to control the spread of informal settlements.

Most commonly, governments acquire land for strategic management through purchases at market prices (Figure 16, panel B). Nonetheless, many governments also acquire land through expropriation. In Latvia for example, land is typically acquired through expropriation to provide public infrastructure, although the government does not have the authority to freeze land prices prior to announcing public involvement. In Ethiopia, public land is scarce and governments acquire land through expropriation, which is in turn used for various purposes including land banking and public land lease. In other countries such as China, Estonia and Turkey, governments already own significant portions of land suitable for strategic management.

Once land is acquired, governments can service the land, provide infrastructure and utilities, and in some cases develop the land for other purposes together with developers (Figure 16, panel C). In some countries however, governments do not participate in direct development. In Australia for example, states acquire vacant or unproductive land in greenfield and brownfield areas, but do not redevelop the land, rather selling land plots to developers at public auctions or leasing for public interest goals. In other countries, strategic land management plays a crucial role in spatial planning and housing policy. As part of the practice of 'active land policy' in the Netherlands for example, strategic land management is carried out by local governments by actively acquiring land in advance of needs for the purposes of urban development and renewal. Local governments not only rezone land and provide basic servicing, but also provision infrastructure and participate in development through joint ventures and public-private partnerships.

Figure 16

Implementation of strategic land management



Note: Multiple responses allowed.

Source: Authors' elaboration based on OECD-Lincoln LVC survey

Implementing LVC: common considerations

While countries' experiences vary significantly, the OECD-Lincoln LVC survey highlights some common issues that need to be addressed for effectively implementing LVC. The following sections discuss some key considerations.

Eliciting public support

The OECD-Lincoln LVC survey highlights how a lack of public support hinders the successful utilisation of LVC. Across all relevant instruments, resistance by property owners was identified as a major obstacle for LVC implementation in the majority of countries surveyed. Understandably, any increase in fees on land and property is likely to be unpopular because such fees are clearly visible. As a result, governments often lack the political will to adopt LVC. Conversely, countries such as Brazil and Colombia have successfully implemented LVC instruments in part due to strong political will that stems from public support and supportive legislation.

Eliciting greater public understanding, support and participation is key to successfully implementing LVC. Land value increments are captured more successfully when communication channels with land owners and stakeholders exist and the benefits from a proposed public intervention are clearly laid out. Landowners may more readily accept contributions to well-chosen projects which raise wellbeing substantially and are perceived to do so. The survey nonetheless highlights how consultation processes with property owners that are affected by LVC instruments are lacking or insufficient in many countries. Providing opportunities for dialogue between affected owners and the government is important to share information and garner public support. For example, communication channels and dialogue are a key component of successful LVC implementation in Japan, where communication procedures are laid out in legislation (OECD, 2022[8]). Dialogue can also be very important when LVC concerns minority peoples that are typically marginalised, such as in the case of indigenous groups whom have different understandings of land (OECD, 2019[11]).

Establishing fair and transparent rules

Establishing clear and fair rules is particularly important for LVC as it involves the potentially contentious agenda of sharing costs to enjoy the benefits of a public good. However, the survey highlights how such legal frameworks are lacking in many countries. The vast majority of countries lack a legal definition of LVC. Clear legislation concerning LVC, its processes, the determination of fees and taxes, affected property owners, and procedures for resolving disputes may reduce conflict, elicit public support, and bring LVC to the political mainstream.

The OECD-Lincoln LVC survey provides insights into how LVC rules can be designed. Examples from Colombia, Finland, and Israel suggest how fees are better accepted by land owners when they are charged in relation to the increase in land values that a public improvement generates, as opposed to when they are charged to simply cover the costs of the improvement. In addition, examples from countries such as Colombia, Ecuador, Mexico, and Sweden emphasise the importance of equity issues. Specifically, these examples highlight how LVC fees are better accepted when they consider the characteristics of landowners, by providing provisions for exemptions or discounts based on socioeconomic status.

Developing local government capacity

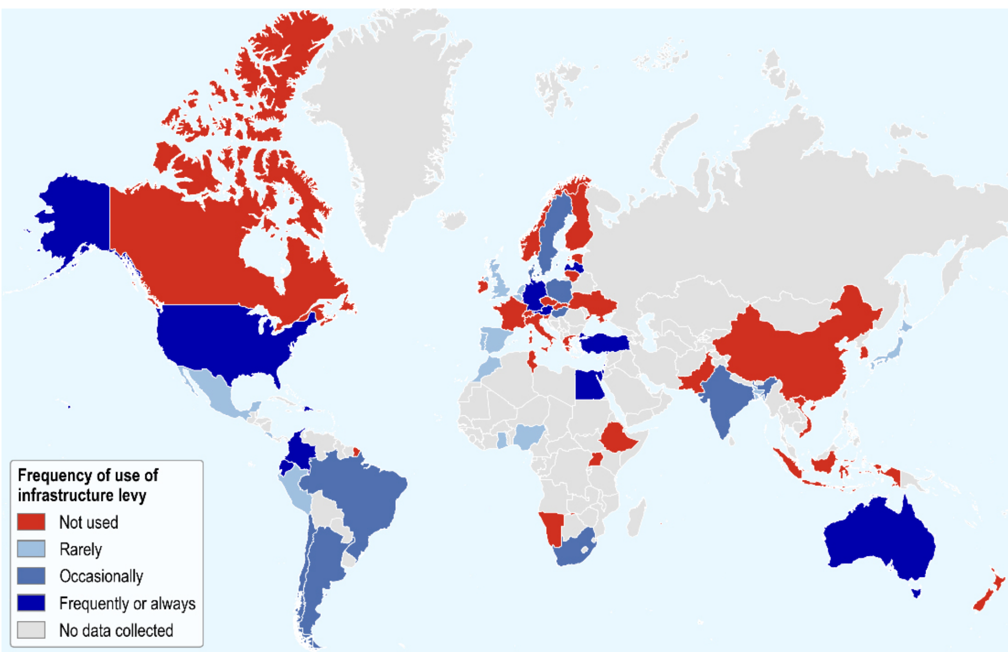
In the majority of countries surveyed, local governments take the leading role in many tasks concerning LVC, including defining land owners affected by the instrument, setting the rates for fees and contributions, negotiating with land owners and developers, and managing land assets, among others. In addition, successful LVC requires sound planning and land use principles.

The OECD-Lincoln LVC survey highlights how a lack of such capacities is one of the key obstacles for successful implementation of LVC across all instruments studied. In particular, local governments in many countries struggle with identifying affected owners and levying fees due to a lack of cadastre and registry data and related expertise. In this context, national governments should provide lower-level governments with adequate administrative support, policy guidelines, and accurate data to facilitate the proper implementation of LVC as a fiscal tool. For example, major cities in Germany (such as Frankfurt) successfully utilise developer obligations to provide for affordable housing, made possible in part due to strong local government capacity stemming from administrative support structures (OECD, 2021[12]). In addition, spatial planning frameworks should clearly define roles of different levels of government in preparing plans and land use regulations that serve as the baseline for LVC administration, such as in the case of Ecuador, Israel, and the Netherlands.

Annex A. Frequency of LVC instrument use across the globe

Annex Figure A.1.

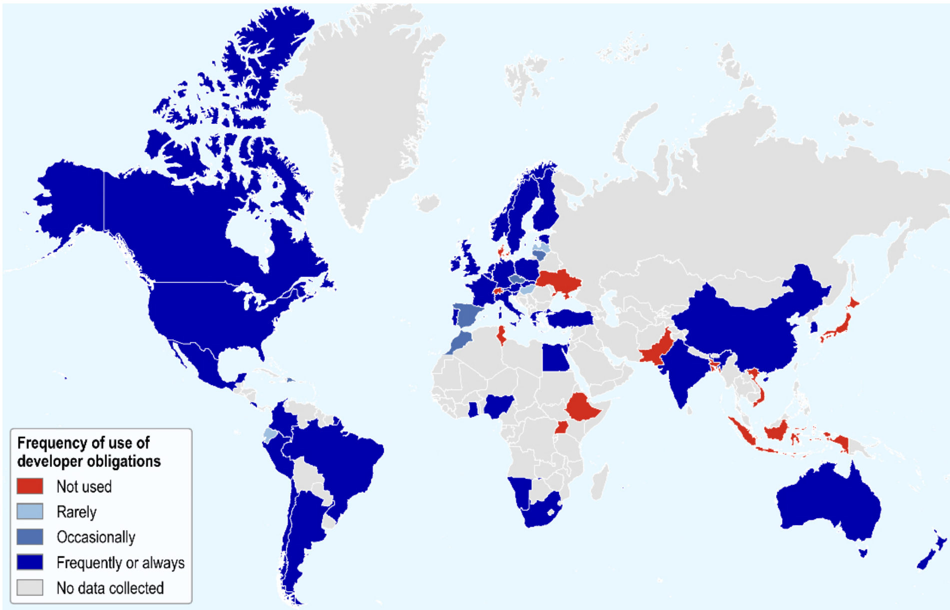
Use of the infrastructure levy by country



Source: Authors' elaboration based on OECD-Lincoln LVC survey

Annex Figure A.2.

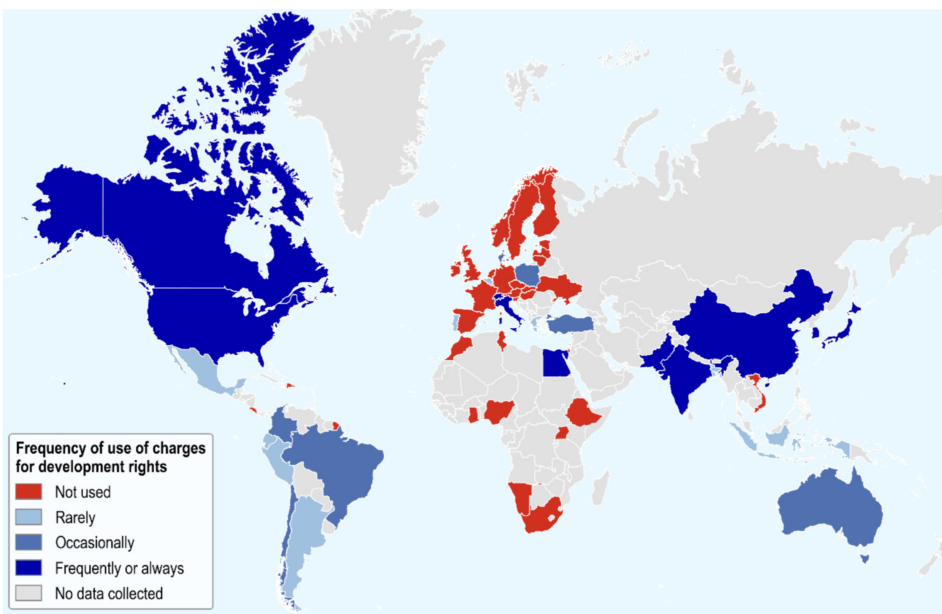
Use of developer obligations by country



Source: Authors' elaboration based on OECD-Lincoln LVC survey

Annex Figure A.3.

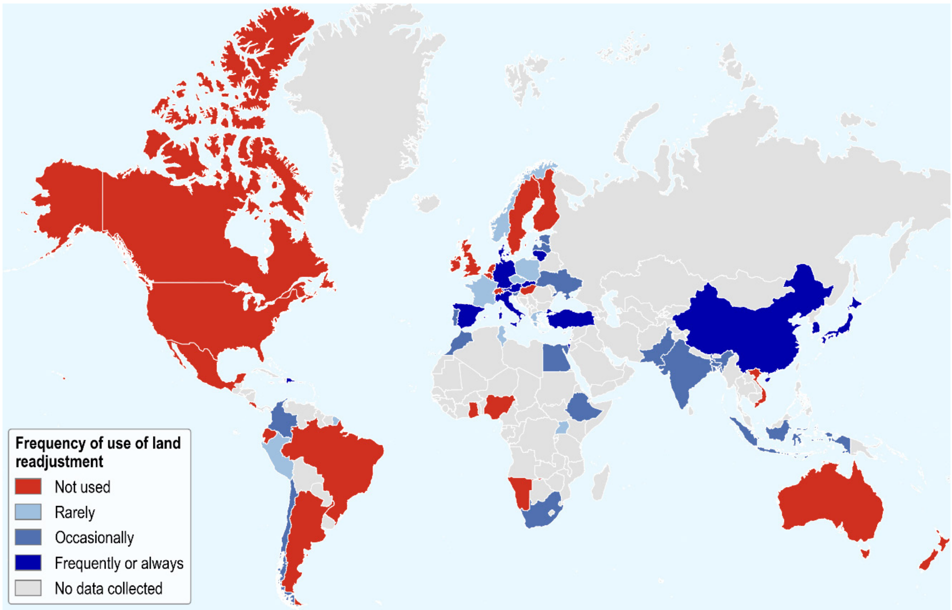
Use of charges for development rights by country



Source: Authors' elaboration based on OECD-Lincoln LVC survey

Annex Figure A.4.

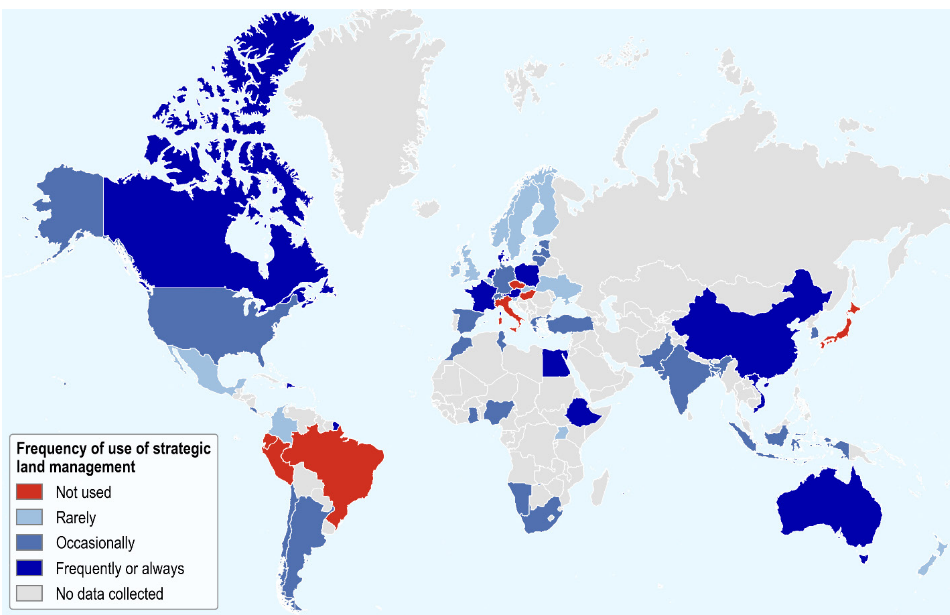
Use of land readjustment by country



Source: Authors' elaboration based on OECD-Lincoln LVC survey

Annex Figure A.5.

Use of strategic land management by country



Source: Authors' elaboration based on OECD-Lincoln LVC survey

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Graphic Detail

Geographic Information Systems (GIS) organize and clarify the patterns of human activities on the Earth's surface and their interaction with each other. GIS data, in the form of maps, can quickly and powerfully convey relationships to policymakers and the public. This department of Cityscape *includes maps that convey important housing or community development policy issues or solutions. If you have made such a map and are willing to share it in a future issue of* Cityscape, *please contact alexander.m.din@hud.gov.*

What Do Visualizations of Administrative Address Data Show About the Camp Fire in Paradise, California?

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The views expressed in this article are those of the author and do not represent the official positions or policies of the Office of Policy Development and Research, the U.S. Department of Housing and Urban Development, or the U.S. government.

Abstract

The Camp Fire destroyed most structures and displaced most of the population in Paradise, California. Since the wildfire, Paradise has returned to approximately one-fourth of its pre-wildfire population. This article visualizes administrative address data before and after the wildfire to measure population displacement and return. Administrative address data is likely underutilized for that purpose.

Camp Fire

On November 8, 2018, electrical transmission lines owned and operated by Pacific Gas and Electric Company (PG&E) sparked the fire that would become the Camp Fire near Pulga, California (Mohler, 2019). The Camp Fire resulted in 85 fatalities, three injuries, nearly 19,000 structures destroyed, and more than 153,000 acres burned (CAL FIRE, 2019). The Camp Fire was the most destructive wildfire to date in California's history (CAL FIRE, 2022), destroyed nearly 90 percent of the housing stock of Paradise and displaced approximately 83 percent of its residents (Kuczynski and Sharygin, 2019). The Camp Fire was estimated to have caused at least $16.5 billion in damages (Munich RE, 2019).

This article examines administrative address data from the United States Postal Service (USPS) to analyze households by mail delivery status in Paradise before, immediately after, and most recently since the Camp Fire. Administrative data offer unique insights into social problems and societal issues that may not otherwise be available to study from traditional social science data sources (Connelly et al., 2016). Substantial work in modeling fire risk has been done using structure data that had to be created, such as the vector building dataset by Microsoft (Ager et al., 2021), and by estimating population migration following a wildfire (Sharygin, 2021). Using existing administrative data may be useful when creating new datasets is expensive, unreasonable, or otherwise not possible.

The purpose of this analysis is to examine what happened to the mail delivery status of residential addresses in the area destroyed by the Camp Fire as a proxy for occupied housing before and after an extreme weather event that destroyed most structures in a community. Developing knowledge and furthering data resources in this domain are particularly important because parts of the United States, including California, have nearly one-half of their housing stock in the wildland-urban interface (WUI) (Hammer, Stewart, and Radeloff, 2007); housing growth inside the WUI outpaces housing growth outside the WUI (Radeloff et al., 2018); and extreme autumn wildfire conditions have increased (Goss et al., 2020). Address data have been used to evaluate population displacement and return following Hurricane Katrina in and around New Orleans, Louisiana (Finch, Emrich, and Cutter, 2010). The USPS may be a good proxy for disaster recovery analysis. Although the USPS has experience reestablishing mail delivery service following an extreme weather event (Stevens, 2005), a lag in the data collection may be present as the USPS works to reestablish service (Plyer, Bonaguro, and Hodges, 2009). USPS address data are likely underutilized and underresearched as a means to analyze population displacement and recovery.

Data

The primary data source for this analysis was administrative address data from the USPS's Address Management System (AMS). Address data are extracted from the AMS at the end of each quarter and aggregated to points at the ZIP+4 geographic level, a highly granular unit of geography.[1] The power of those data is that they are collected daily from letter carriers that visit each address, are promptly made available, are available at the near-address level, and can be aggregated to any level

[1] In Paradise, California, a single ZIP+4 point contained 1–24 residential addresses.

of administrative geography or used as points. The USPS categorizes residential addresses where mail is not being collected into two categories:

1. Vacant: Mail has not been retrieved for at least 90 days. This category is typically further separated into two levels of vacancy (Harrison and Immergluck, 2021):

    a. Short-term vacant (6 months or less): Potential healthy levels of vacancy, such as unit turnover.

    b. Long-term vacant (6 months or more): An indicator of abandoned housing and an unhealthy housing market.

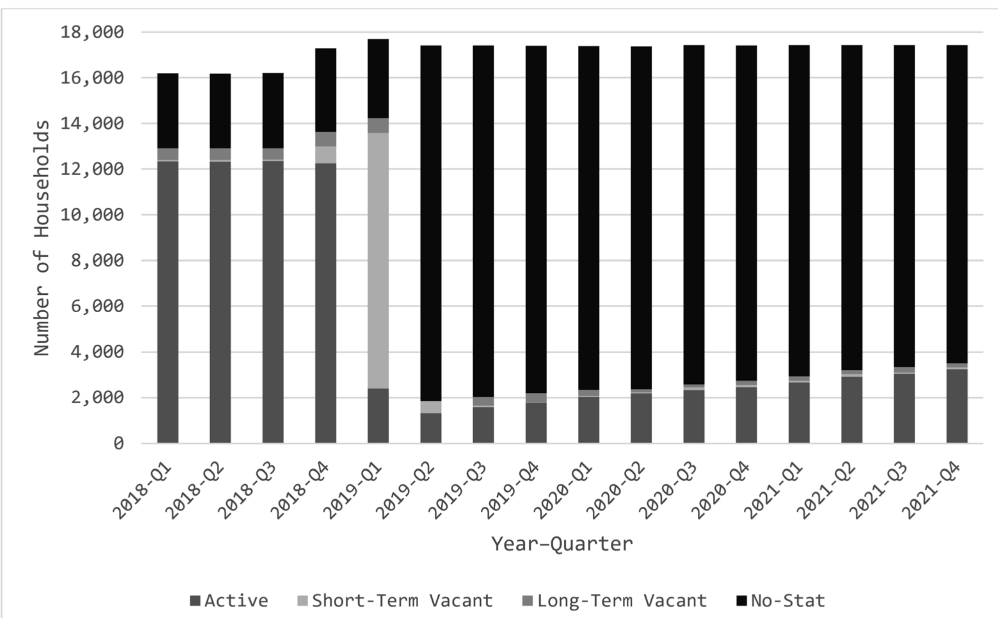
2. Not-a-statistic (no-stat): Mail has not been retrieved for at least 90 days, the address has been demolished, the address has been merged with another address, the address is under construction and not yet receiving mail, or unlisted other possibilities (HUD, 2010).

Active residential addresses are calculated as addresses that are neither vacant (for any term) nor no-stat. These addresses are a proxy for occupied housing.

Household mail delivery status for Paradise, California, is shown in exhibit 1. In the three quarters before the Camp Fire, Paradise had approximately 12,300 active residential addresses, fewer than 100 short-term vacant residential addresses, about 500 long-term vacant residential addresses, and nearly 3,300 no-stat residential addresses. The Camp Fire occurred during the fourth quarter of 2018.

Exhibit 1

Residential Addresses by Mail Delivery Status in Paradise, California (2018–2021)



Source: HUD Aggregated USPS Administrative Data on Address Vacancies; 2018–2021; analysis by author

The data extract for that quarter was pulled more than a month after the wildfire was contained, but the number of active, long-term, and no-stat residential addresses remained roughly the same. The number of short-term vacant addresses increased by nearly ten-fold, to 662; however, that number is far short of the nearly 19,000 structures that were destroyed by wildfire.

Data for the first quarter of 2019 were extracted from the AMS on March 31, 2019, more than 4 months after the Camp Fire was contained. The number of long-term vacant (662) and no-stat (3,460) residential addresses remained similar to previous quarters. Short-term residential vacancies grew to more than 11,000, and the number of active residential addresses fell to roughly 2,400, suggesting that occupied housing fell to 19.4 percent of homes that were occupied at the end of the third quarter of 2018, immediately before the fire; that percentage is consistent with the estimate that 83 percent of Paradise's population was displaced (Kuczynski and Sharygin, 2019).

Most non-active residential addresses were listed as no-stat addresses in the second quarter of 2019. Residential addresses actively receiving mail declined to its lowest count—slightly more than 1,300, a decrease of 89.2 percent from before the fire. The number of short-term vacant and long-term vacant homes decreased significantly.

From the second quarter of 2019 to the first quarter of 2021, active residential addresses increased from slightly more than 1,300 to more than 3,200, an increase of more than 144.7 percent since the lowest point of active residential housing units in the second quarter of 2019. This count of active residential addresses represents roughly one-fourth (26.2 percent) of active residential residences before the Camp Fire. The numbers of short-term vacant and long-term vacant residential addresses remained roughly stable throughout this period. No-stat residential addresses decreased at roughly the same rate as active residential addresses increased, and the number of total residential addresses remained around 17,400.

Maps

The maps shown were produced using dot densities instead of the ZIP+4 points. Dot density maps are a common method for showing counts of data, particularly population location and density (Gomes, 2016). Because ZIP+4 points are relatively close together and represent relatively few residential addresses, breaking up a ZIP+4 point into multiple, smaller dots to visualize the location of residential addresses allows for a close approximation of residential addresses at the scale of viewing all of Paradise together. Dot density maps were created to visualize the density of occupied housing units before, immediately after, and most recently since the Camp Fire. Several steps were taken to produce the maps:

- Because ZIP+4 points can have the same latitude and longitude coordinates as other ZIP+4 points, ZIP+4 points that were stacked on other ZIP+4 points were collapsed into a single point[2] (a collapsed ZIP+4 point).

[2] For the third quarter of 2018, this activity reduced the number of ZIP+4 points from 3,433 to 2,926 unique points. The number of residential addresses—of a mail delivery status—stayed the same.

- To represent the developed outline of Paradise and contain the area in which dot density points could be created, a convex hull[3] of the collapsed ZIP+4 points was created. A convex hull is the smallest shape that contains a set of features—in this case, collapsed ZIP+4 points. Edits to the polygon were made to remove sections without housing to restrict possible dot density placement further.
- Thiessen Polygons[4] were created from each collapsed ZIP+4 point; the attributes of each collapsed ZIP+4 point persisted to each respective Thiessen Polygon.
- The Thiessen Polygons were clipped by the edited convex hull.
- The dot density of each Thiessen Polygon after the clip was mapped.

The resulting clipped Thiessen Polygons for each collapsed ZIP+4 point had a median area of 2.5 acres, or approximately 0.64 acres per residential address of any mail delivery status. Finally, each clipped Thiessen Polygon was mapped by dot density by the number of occupied residential addresses, which is defined as any household actively receiving mail (not vacant or no-stat). The dots do not draw in the exact location of any particular address, but the area on which each set of dots can be generated is very small and thus reflects near-location placement.

Exhibit 2 visualizes the presence of active residential addresses in Paradise as of September 30, 2018, about a month and a half before the fire. Each dot represents one active residential address, and the exhibit shows more than 12,200 such addresses. Housing is generally dispersed throughout the community except at some of the city limits and in the far southern area. This map serves as the benchmark for active residential addresses before the Camp Fire.

[3] The tool Minimum Bounding Geometry in ArcGIS Pro was used to create the convex hull, see https://pro.arcgis.com/en/pro-app/2.8/tool-reference/data-management/minimum-bounding-geometry.htm for further information on the tool.

[4] The tool Create Thiessen Polygons in ArcGIS Pro was used to create the Thiessen Polygons; see https://pro.arcgis.com/en/pro-app/2.8/tool-reference/analysis/create-thiessen-polygons.htm for more information on the tool.

Exhibit 2

Active Residential Addresses in Paradise, California (September 30, 2018)

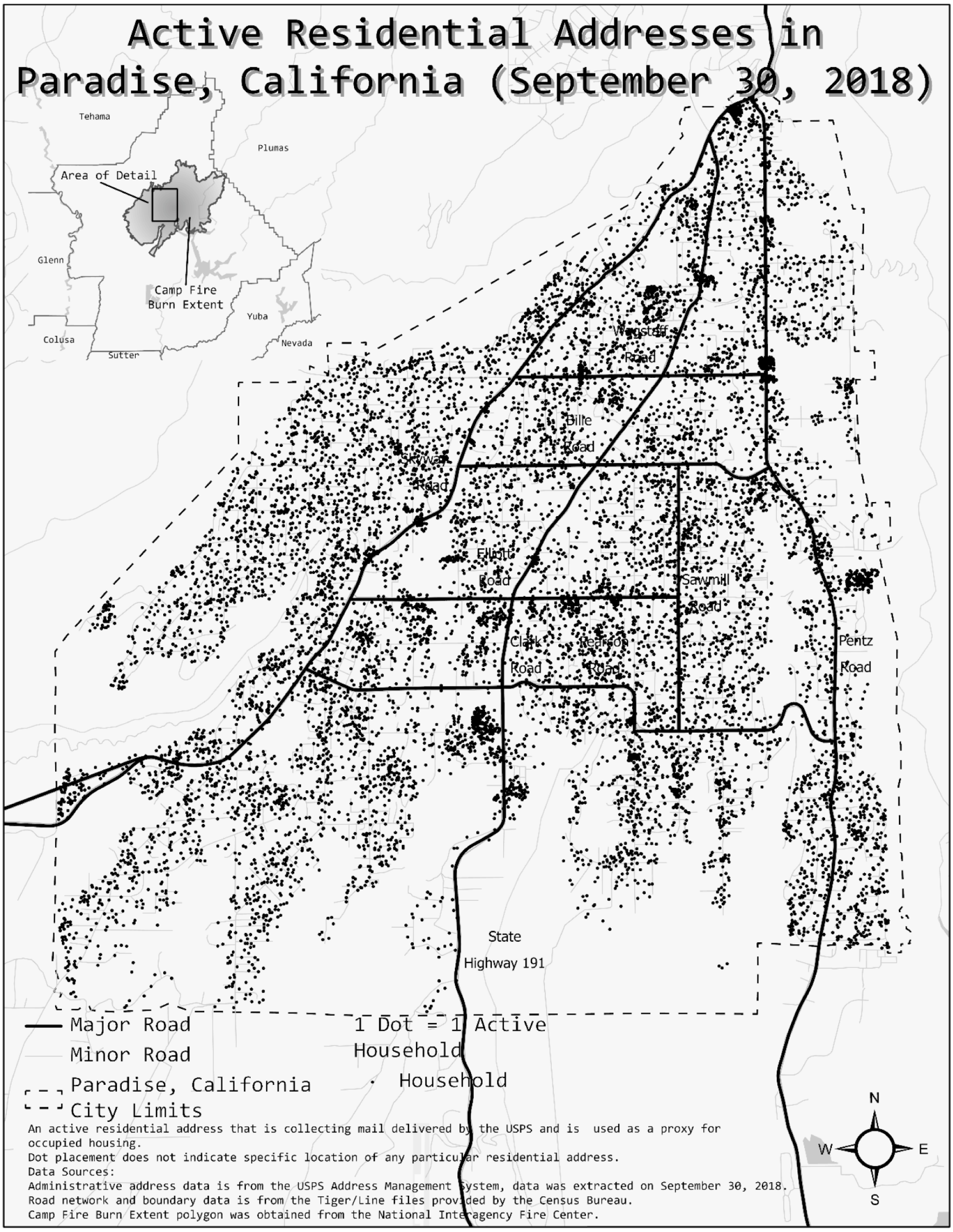


Exhibit 3 shows the presence of active residential addresses in Paradise on June 30, 2019, about seven months after the wildfire. Active residential addresses have been reduced from more than 12,200 to slightly more than 1,300—an 89.2-percent reduction. Housing has been reduced in all sections of Paradise. Few clusters of dense housing remain, particularly along Clark Road to the northwest of the intersection with Peterson Road and near the intersection with Wagstaff Road. A visual inspection of the map shows such a drastic reduction in active residential addresses throughout Paradise that it is difficult to pick any particular section to describe.

Exhibit 3

Active Residential Addresses in Paradise, California (June 30, 2019)

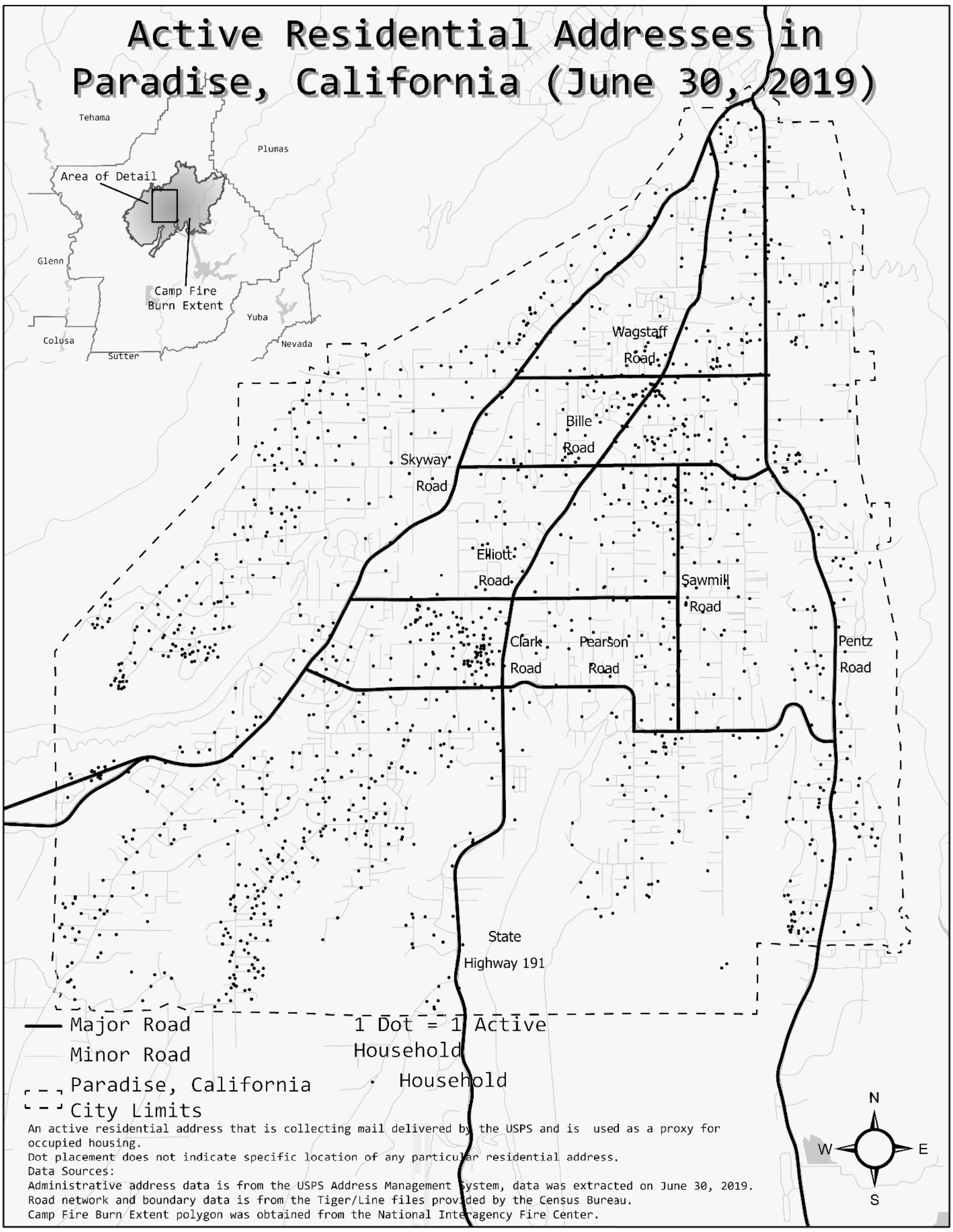
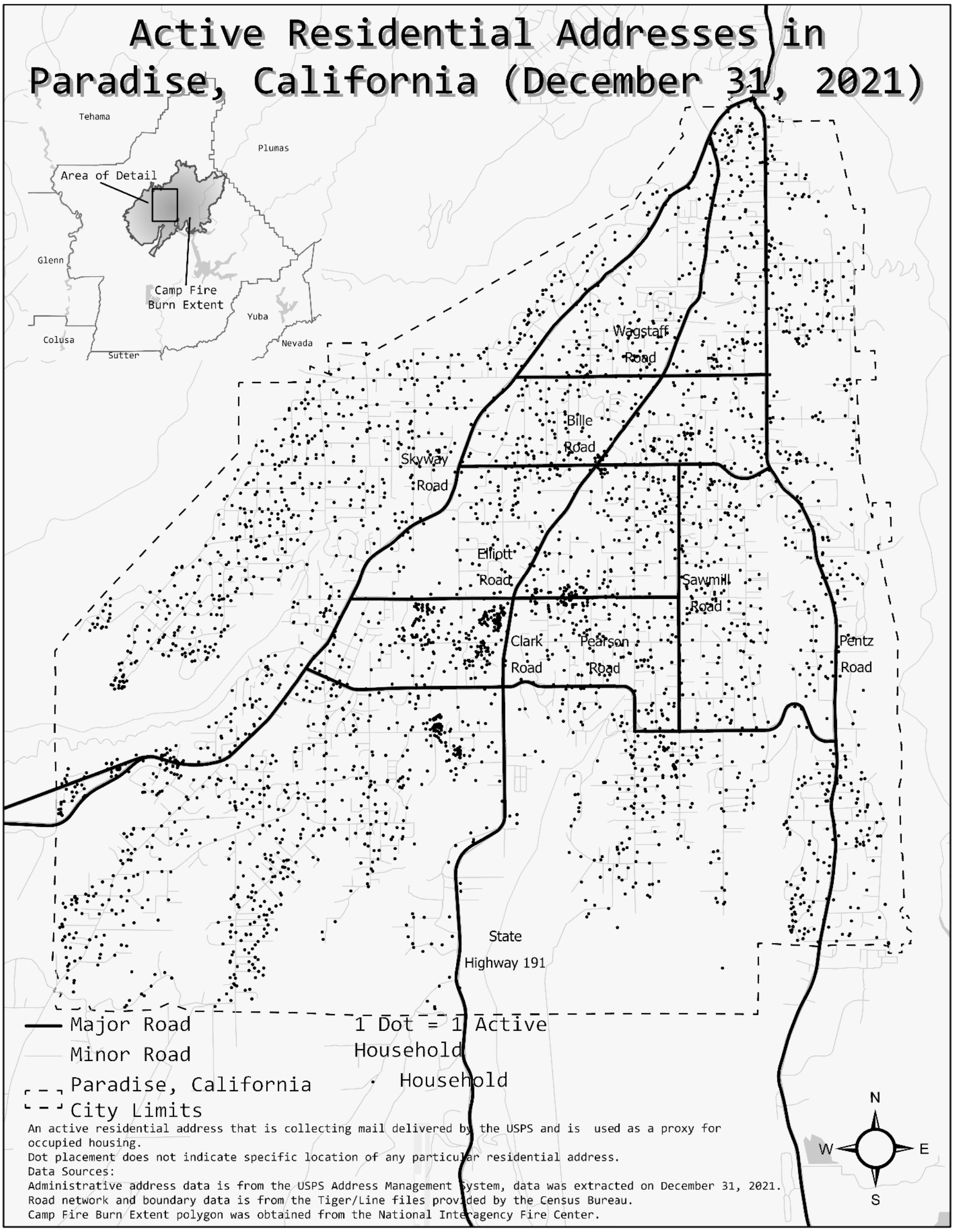


Exhibit 4 displays a dot density map for active residential addresses as of December 31, 2021, the date of the most recently available data at the time this article was written. Active residential addresses have grown to more than 3,200, an increase of 144.7 percent since the lowest count at

Exhibit 4

Active Residential Addresses in Paradise, California (December 31, 2021)



the close of the second quarter of 2019. This increase represents slightly more than one-fourth (26.2 percent) of homes that were assumed to be occupied before the Camp Fire. Growth in active housing appears to have occurred throughout Paradise. Clusters of active housing are present to the east and west of Clark Road, particularly along Elliott Road. Even with the high rate of return of active housing, the density of dots is far less than before the Camp Fire.

Conclusion

This article is a high-level overview of the potential for analyzing administrative address data before and after an extreme weather event has destroyed the majority of a community's housing stock. Numerous possibilities exist for researchers, analysts, and policymakers to further the use of these data for monitoring and evaluating population displacement and recovery in the wake of extreme weather events, particularly as such events are predicted to increase (Keyser and Westerling, 2017). Researchers, planners, policymakers, and other interested parties should take note of administrative address data as a data source to evaluate population displacement and return, particularly when other data sources may not be available or when other data sources are slower to capture population mobility trends (Sharygin, 2021).

Topics for further research might include, but are not limited to, the following:

- More in-depth and sophisticated spatial analysis of population displacement and recovery in Paradise, California, or other communities affected by wildfires and other extreme weather events to further understand the geography of population return.
- Spatial analysis of the growth of housing in the Wildland Urban Interface.
- Data linkage with destroyed structure survey data or construction permit data to further understand how to best monitor and evaluate administrative address data following a disaster, such as a wildfire, for population displacement and return.
- Data linkage with other datasets, such as NASA's Nighttime Lights dataset, which has served as a proxy for human development (Bruederle and Hodler, 2018).
- Analysis of administrative address data across multiple extreme weather events that result in population displacement but not necessarily the destruction of housing.
- Spatial analysis of administrative address data following disaster events, such as tornadoes, poses unique challenges due to the highly localized destruction.
- Comparison of population mobility trends, such as school enrollment or other administrative data that capture record-of-home changes.

Author

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The U.S. Department of Housing and Urban Development sponsors or cosponsors three annual competitions for innovation in affordable design: The Innovation in Affordable Housing Student Design and Planning Competition; the American Institute of Architects – HUD Secretary's Housing Community Design Awards; and the HUD Secretary's Opportunity & Empowerment Award, co-sponsored with the American Planning Association. This Cityscape *department reports on the competitions and their winners. Each competition seeks to identify and develop new, forward-looking planning and design solutions for expanding or preserving affordable housing. Professional jurors determine the outcome of these competitions.*

2022 Innovation in Affordable Housing Student Design and Planning Competition: The Housing Authority of the City of Atlanta, Georgia

Alaina M. Stern
Office of Policy Development and Research
U.S. Department of Housing and Urban Development

The Jury:
Jamie Bordenave (Head Juror)—Founder and President, The Communities Group
Dana Cuff—Director, cityLAB, and Faculty, Dept. of Architecture and Better Urban Design, University of California, Los Angeles
Carlos Martin—Project Director of the Remodeling Futures, Harvard University's Joint Center for Housing Studies, Rubenstein Fellow, The Brookings Institution.
Mariela Alfonzo—Founder and Chief Executive Officer, State of Place
Jesse Wiles—Principal, Chief Executive Officer, APD Urban Planning and Management
Cody Owens—Housing Preservation Specialist, Dominion Due Diligence Group

Winning Team—University of Maryland, "Rise of Pines"
Danielle Abe
Fadi Alajati
Maria Fernanda Farieta
Samuel McCormally
Donald Nuzzio

Runner-Up Team—University of California, Berkeley, "Civic Oaks"
James Chang
Norris Cooper
Emiliano Farina
Angela Miki Kobayashi
Brice Lockard

Introduction

The ninth annual U.S. Department of Housing and Urban Development's (HUD's) Innovation in Affordable Housing (IAH) Student Design and Planning Competition challenged multidisciplinary graduate student teams to respond to an existing affordable housing design and planning issue. Teams were composed of graduate students in architecture, planning and policy, finance, business, and other disciplines. The competition required students to address the social, economic, and environmental issues in responding to a specific housing development problem identified by a partnering public housing agency (PHA).

For the 2022 challenge, HUD partnered with The Housing Authority of the City of Atlanta, Georgia (AH), to challenge the competitors to create innovative solutions for redeveloping the Boisfeuillet Jones Atlanta Civic Center complex and the land it sits on (exhibit 1). Teams were asked to find solutions to convert the 13.12 acres of developable land into affordable housing in a mixed-use and mixed-income setting while preserving the cultural, historical, and social significance of the Civic Center. The four finalist teams balanced several factors—including the local planning context, zoning requirements, local economic conditions, the area's historical and cultural significance, the built environment, and the larger social needs of the community—to create their final proposals, which had to include a feasible financing plan for their development.

The overarching goal of this year's competition was to advance innovation in the design of affordable housing. Student proposals contained potential solutions that could be implemented on site, and the plans were to promote durability, reduce energy consumption, increase the quality of housing, and enhance the social and economic vitality of the surrounding community.

Atlanta Housing (AH) is not only the largest housing authority in Georgia, it is one of the largest in the nation, providing and facilitating affordable housing resources for more than 23,000 low-income households. AH has continued to help provide low-income individuals with affordable housing options through services and resources, including AH-owned residential communities; AH-sponsored mixed-income, mixed-finance residential communities; tenant-based vouchers; HomeFlex Program (formerly Project Based Rental Assistance Program); supportive housing arrangements; and homeownership opportunities.

Exhibit 1

Site map of the Boisfeuillet Jones Atlanta Civic Center complex, showing the (1) Auditorium, (2) Exposition Center, (3) Plaza, (4) Stormwater Vault, and (5) Southface Institute

The site was originally home to Buttermilk Bottom, a community of approximately 16,000 people that took root in the early 1900s. Today, the Boisfeuillet Jones Atlanta Civic Center is at the nexus of Downtown, Midtown, SoNo, and the Old Fourth Ward neighborhood in Atlanta, Georgia. In 2017, AH took ownership and acquired the site; however, the facilities have not been open to or operating for public use since 2006. The complex includes a Performing Arts Center and a 125,000-square-foot Exhibition Hall. Both buildings' entrances center on a formal plaza and fountain, continuing the tradition of cultural institutions serving as both an iconic landmark and a public amenity for residents. AH envisions the site's transformation will be a truly vibrant, mixed-use community that includes affordable and market-rate housing along with office, retail, hospitality, and open space that seamlessly integrate into the existing cultural facilities intended to remain on site.

The competition was designed in two phases. In phase I, a jury of five practitioners evaluated the first-round proposals submitted electronically by graduate student teams. The jury deliberated on the 10 highest-scoring teams to select the four finalists that would move on to phase II of the competition. In phase II, the four teams further refined their proposals—addressing complex issues, incorporating more detail, improving their design plans, and conducting additional analyses on the financing needed to create viable housing, following an in-person site visit to Atlanta.

In March 2022, students from each of the four finalist teams traveled to Atlanta for a 2-day site visit, accompanied by Calvin Johnson, deputy assistant secretary of HUD's Office of Policy Development and Research (PD&R), and PD&R staff. AH guided students on a tour of the entire Civic Center complex and its surrounding property, including a stormwater vault adjacent to the auditorium. Students had the opportunity to explore the inside of the auditorium, which features a large performance hall that once seated nearly 4,600 patrons, and the exhibition building, which once held educational, arts, and science exhibits. The students met with local officials, AH executives, AH financing and planning partners, city commissioners and council members, community members, and affordable housing advocates who spoke to the site's history, shared personal stories, and communicated their hopes and aspirations for the site (exhibit 2).

Exhibit 2

Students, guest speakers, and HUD staff during site-visit to Boisfeuillet Jones Atlanta Civic Center, pictured outside in the plaza in front of the auditorium

Several weeks after the site visit, the four finalist teams presented their revised proposals virtually, on April 13, 2022, in the Final Presentations and Awards Ceremony. At that event, the finalist teams presented revised project plans to the panel of jurors and an audience. Audience members included AH staff, city officials, local community members, and HUD leadership and staff. The event was streamed live for public viewing. Each student team delivered a 20-minute presentation addressing how their plans respond to the economic, social, and environmental challenges of the development site. The students then had 10 minutes to field questions from jurors. Following the presentations, the jury selected the University of Maryland team as the winner and the University of California, Berkeley team as the runner-up (exhibit 3).

Exhibit 3

Winning team—University of Maryland Team pictured at virtual Awards Ceremony

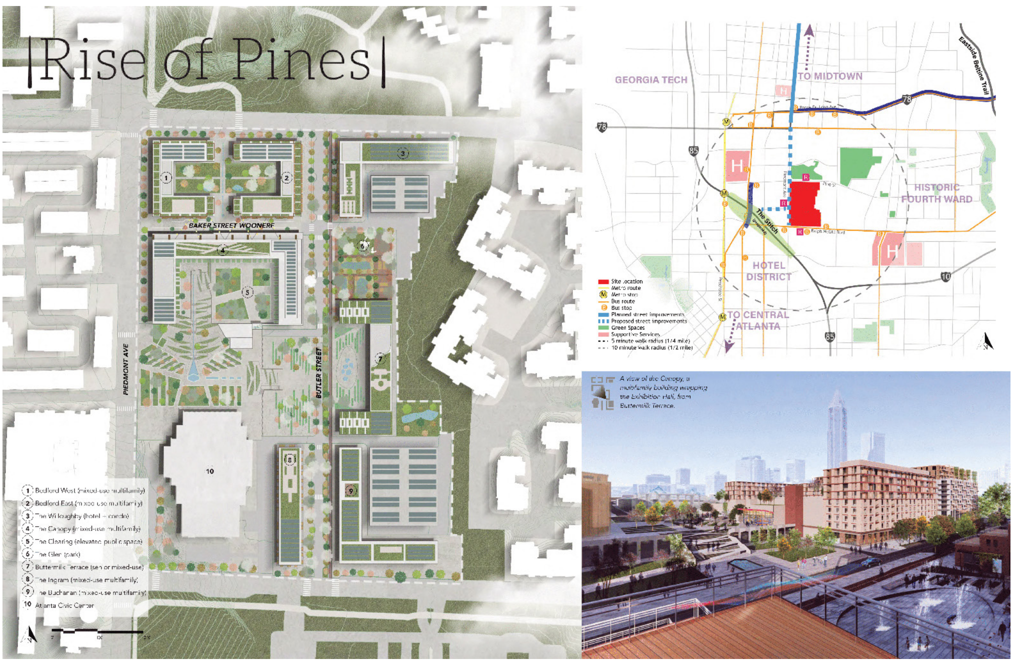
The jurors praised the University of Maryland team for their incorporation of thoughtful and purposeful architecture, sustainability initiatives, and human-centered design. The four finalist teams were addressed by Dominique Blom, general deputy assistant secretary of HUD's Office of Public and Indian Housing, who welcomed and encouraged the students, stating, "I hope that this competition has inspired you to begin your careers in housing and community development because we need people like you in this field." Further, Adrianne Todman, HUD deputy secretary, congratulated all four finalist teams and shared her hopes for the students. Eugene Jones, Jr., president and chief executive officer of AH, also spoke to the student finalists and offered his sincere appreciation for the students' hard work and enthusiasm for the site's potential and future.

The Winning Team: University of Maryland

Danielle Abe, Fadi Alajati, Maria Fernanda Farieta, Samuel McCormally, Donald Nuzzio

Exhibit 4

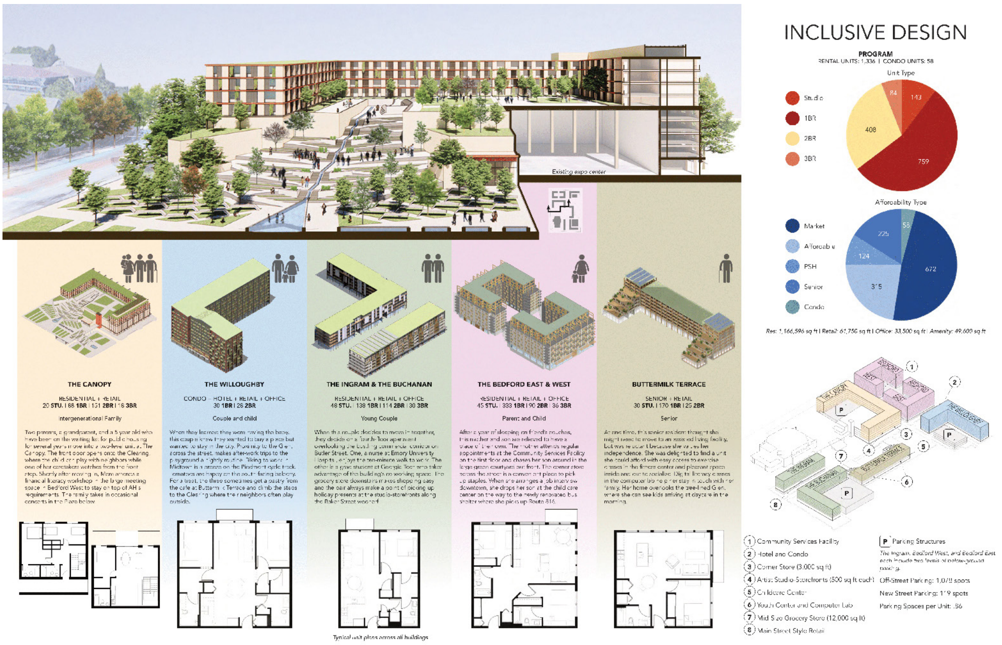
Rise of Pines



The University of Maryland team presented their winning proposal, "Rise of Pines," during HUD's 9th Annual Innovation in Affordable Housing Student Design and Planning Competition (exhibit 4). The team's design addresses the need for a true mixed-use, mixed-income community in the heart of Atlanta, Georgia, in a neighborhood that is rapidly gentrifying and losing its supply of affordable housing. In aligning with existing plans and regulations, which aim to create a dense urban texture in Atlanta's Historic Fourth Ward, Rise of Pines proposed 1,394 residential units across seven structures: three cross-laminated timber high-rise buildings and four wood-frame mid-rises.

Exhibit 5

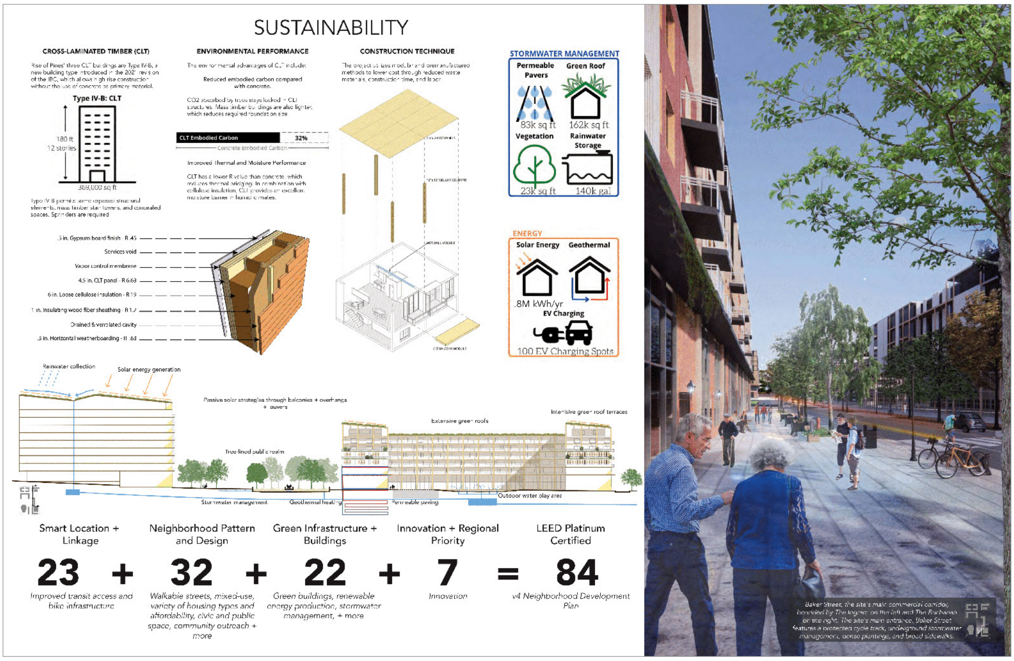
Rise of Pines' Building and Design Features



The central design feature of Rise of Pines is the integration of Atlanta's existing Exhibition Hall into the site (exhibit 5). The northern half of the Exhibition Hall would be demolished at an existing expansion joint. The roof of the Exhibition Hall is reimagined as a 1-acre park connected to the Civic Center Plaza by a terraced network of water, plants, stairs, and wheelchair-accessible ramps. The Rise of Pines structures are designed to be compatible with the EarthCraft program for multifamily homes, and the site could be certified Platinum under the LEED for Neighborhood Design v4 guidelines (exhibit 6). Solar panels and geothermal heat pumps, supported by tax credits, would reduce the project's carbon footprint.

Exhibit 6

Rise of Pines' Sustainable Practices and Design Elements



Rise of Pines proposes housing options for low and very low-income households, recently homeless people, seniors, and working families in an amenity-rich environment with abundant open spaces. The project relies on funding from 4 percent and 9 percent Low-Income Housing Tax Credits (LIHTCs). It would be competitive for 9 percent LIHTCs due to its amenities, transit accessibility, and wide range of services for disabled and elderly residents, and it also would be eligible for a 30-percent basis boost due to its location in a Qualified Census Tract, Difficult Development Area, and New Markets Tax Credit area.

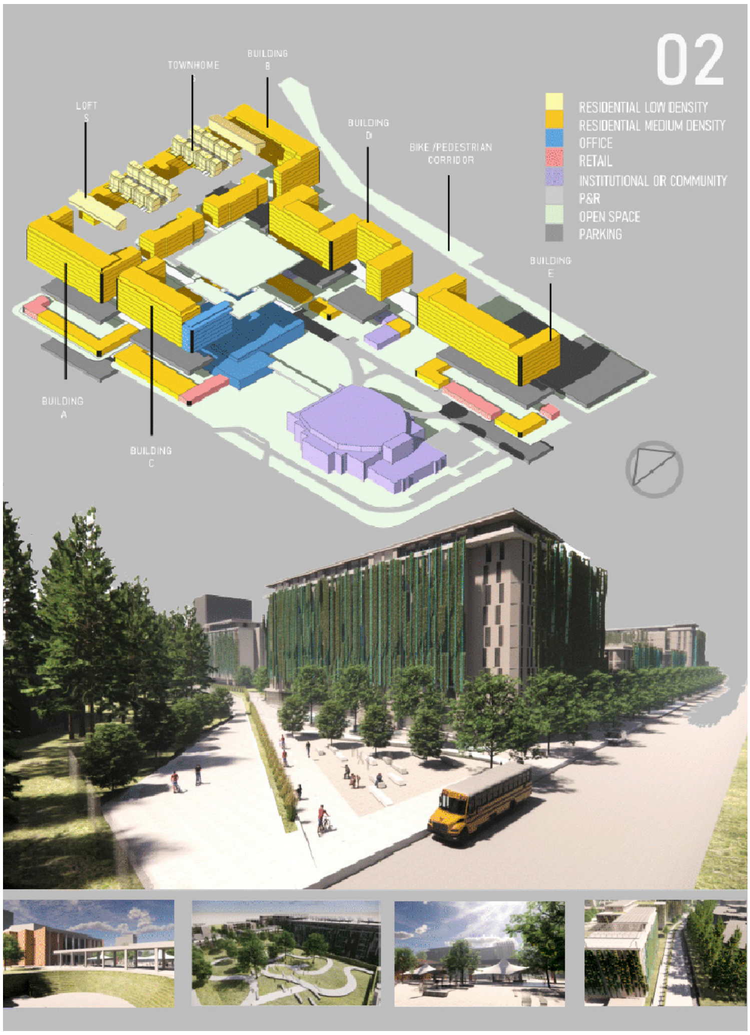
The competition jurors praised the team for their focus on construction and design. The jurors also commended the University of Maryland team for their utilization of the topography of the site and for innovative methods of construction, financing, and organization.

The Runner-Up Team: University of California, Berkeley

James Chang, Norris Cooper, Emiliano Farina, Angela Miki Kobayashi, Brice Lockard

Exhibit 7

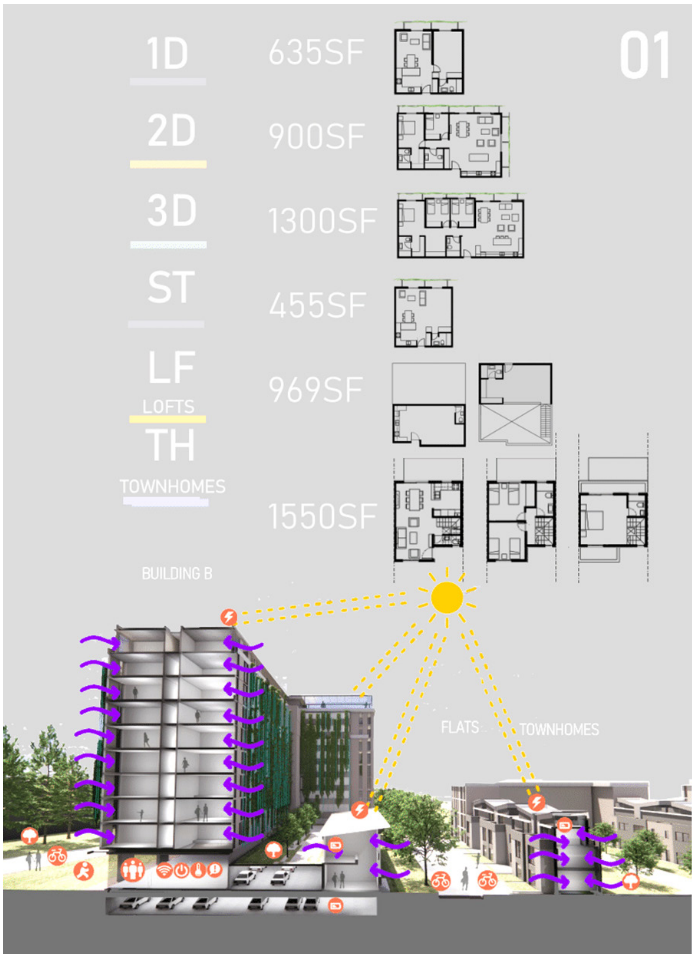
Civic Oaks' Plan and Proposed Site Map



The University of California, Berkeley's Civic Oaks plan was selected as the runner-up (exhibit 7). The team's Civic Oaks development was a collection of more than 748 new residences, approximately 80,000 square feet of office space, 500,000 square feet of green and open space, and 14,600 square feet of retail space that would enhance the culture and unique flavor of Atlanta's Old Fourth Ward. The Berkeley team envisioned transforming the 13+ acre site into a vibrant mixed-use community by using open spaces to integrate the existing cultural facilities and the old Civic Center event space.

Exhibit 8

Civic Oaks' Housing Unit Typologies



Their vision includes subdividing the current "super-block" into smaller, neighborhood-scale streets (exhibit 8). The team considered community opposition to highrise construction and created a medium-height ensemble of buildings. Civic Oaks incorporates various housing types and unit sizes, from studios to three-bedroom units, condominiums, townhomes, and live-work lofts. A centerpiece exposed amphitheater in the central plaza would serve the community through a combination of cultural, educational, and art programs intended to promote community health.

The development plan designates more than 50 percent of the homes to be affordable for low-, moderate-, and middle-income households, with one building set aside specifically for large, family-affordable housing and 28 units for integrated permanent supportive housing. The project uses a wide range of financing to achieve feasibility. Located in a census tract with a 2.5-percent rental vacancy rate—more than 1 percent lower than Atlanta and Fulton County's rates—Old Fourth Ward has a demonstrated need for more housing.

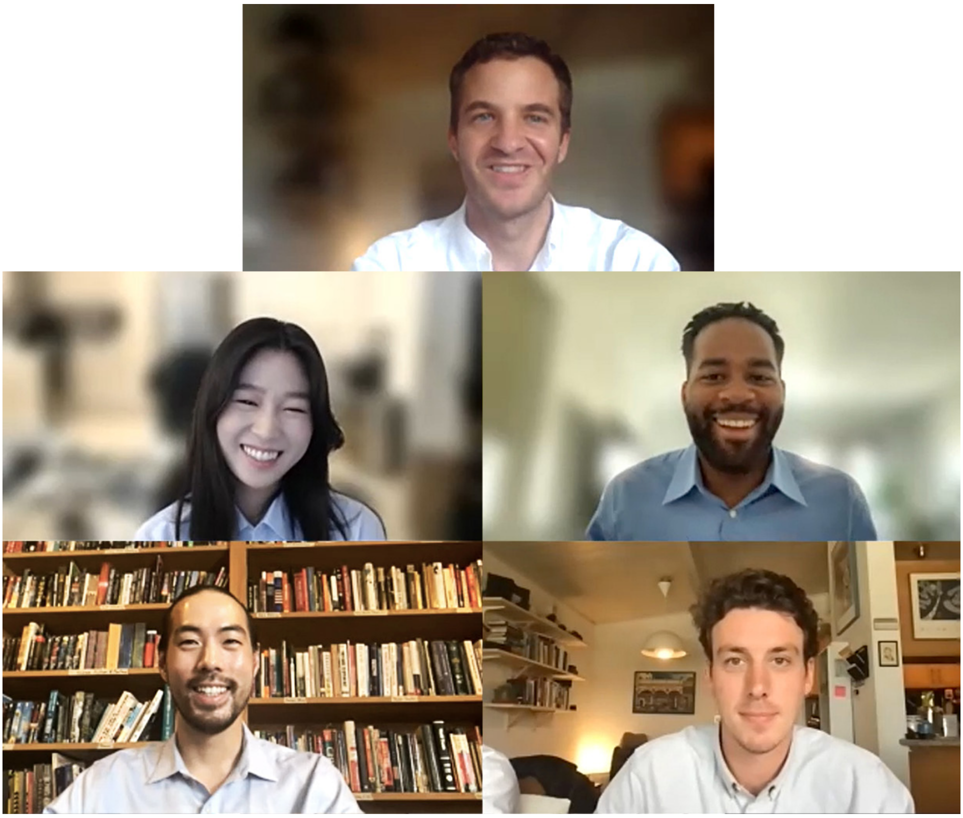
Exhibit 9

Civic Oak's Architecture, Design Features, and Sustainable Practices

The proposal's inclusion of open space and landscaping design was specifically inspired by community input from the Atlanta Civic Center's Neighborhood Planning Unit and the Fourth Ward West Neighborhood Association (exhibit 9). Embracing Atlanta's reputation as a City in a Forest, the proposal seamlessly incorporates a network of green spaces. Civic Oaks would keep the existing oak trees around the site, maintaining old growth foliage. The team's design embraces the context of the existing urban fabric and would pioneer modern sustainable construction practices (exhibit 10).

Exhibit 10

Runner-up team from the University of California, Berkeley, pictured at virtual Awards Ceremony



Thoughts from the Jury

Jamie Bordenave (Head Juror), Dana Cuff, Carlos Martin, Mariela Alfonzo, Jesse Wiles, Cody Owens

The jury for the 2022 IAH Student Design and Planning Competition faced the difficult task of deciding which of the four outstanding finalist teams' site plans best exemplify an innovative design. The jury members were asked specifically to consider how well the student teams successfully and convincingly addressed the following critical elements:

- Is the proposed design reasonable and feasible in its design and planning, demonstrating knowledge and understanding of building codes and zoning?
- Is the proposed design resilient and environmentally responsive to the local climate?
- Is the proposed solution affordable (cost effective to construct and operate)?
- Does the design innovate in a way that integrates the design into the neighborhood and community?

- Does the design promote social responsiveness, such as creating a sense of neighborhood or cohesive community, facilitating access to employment and services, addressing accessibility, and demonstrating the opportunity for social networking, ownership, and comfort?
- Is the approach innovative in all aspects of the solution (for example, planning, design, construction, environmental concerns, and durability)?
- Does the proposal recommend innovative strategies in addressing the needs of the surrounding community and neighborhood?
- Were innovative approaches employed to integrate the design into the neighborhood and community?

The jurors found that two of the four team proposals addressed nearly all the critical elements clearly and with forethought. Jurors narrowed down the four finalist projects to two teams: one from the University of Maryland and the Team Gold from University of California, Berkeley. Both teams had strong proposals. Jurors were impressed with Berkeley's approach to community engagement and their attention to the community. Their design includes feedback from the community; it includes 40,000 square feet of landscape space within the site, creating a highly engaging gathering spot with multiple uses, as well as three-bedroom units, which had been identified as a need by the local residents. Although jurors were extremely impressed by the scale and massing that Team Gold from University of California, Berkeley was able to achieve with their design, the jury agreed that University of Maryland's design both met the housing supply goals and had stronger architectural features.

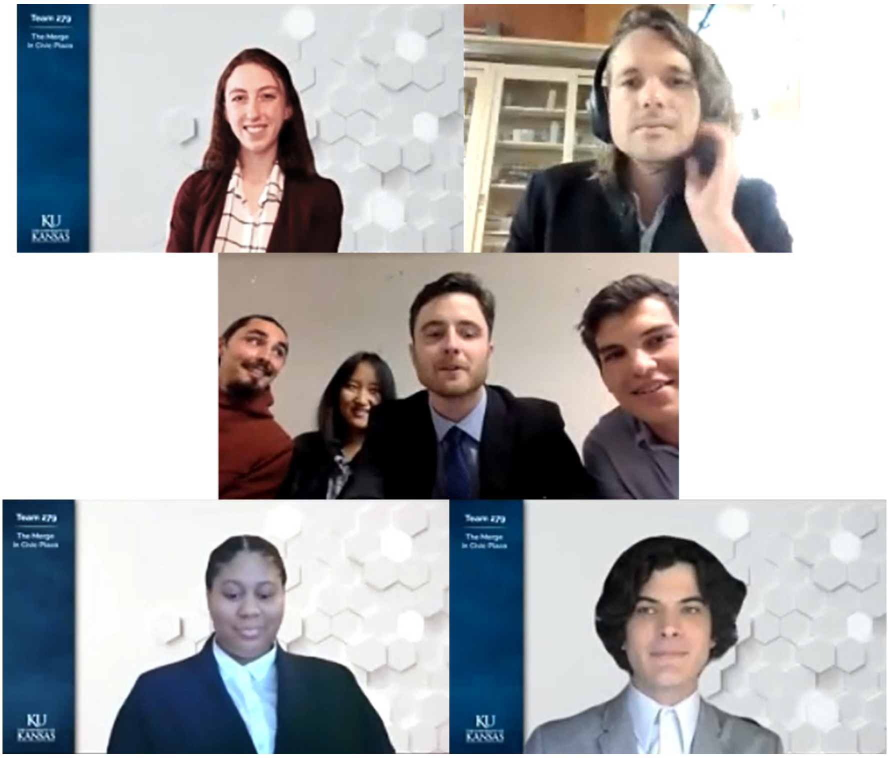
The jurors chose the University of Maryland team's design for the focus and incorporation of human-centric design and, from a sustainability perspective, an innovate use of land. The jury thought that their innovative use of the site's topography, a factor that was a real challenge, was excellent. The proposal also stood out to the jury for its incorporation and "wonderful focus on construction and design, particularly the innovative use of cross-laminated timber."

Acknowledgments and Honorable Mentions

The U.S. Department of Housing and Urban Development would like to thank the remaining two finalist teams for their competition and contributions during the final event: Team KU 1 from the University of Kansas and the University of California Berkeley Team (exhibit 11).

Exhibit 11

Two remaining finalist teams from the University of Kansas and the University of California, Berkeley, pictured at virtual Awards Ceremony



- Team KU 1, University of Kansas (John Hardie, Inbal Hazlett, Samara Lennox, Karen Lewis, and team lead Elizabeth Overschmidt): The team's proposal includes a solution that presents a healthy and sustainable community and reconnects the street network to increase the neighborhood's walkability. In addition, several housing types and price points are provided in a mixed-use, mixed-income community that features a health clinic intended to operate in collaboration with the local university health center. The jurors enjoyed and appreciated the innovation of the University of Kansas designs, including the method they proposed to reintroduce a street that would break up the super-block and promoted ground-floor commercial uses within the complex.

- Team Oski, University of California, Berkeley (Samuel Day, Joseph Mutter, Dylan Rodolf, team lead Andrew Stasiuk, and Shiying Wang): The team's plan was proposed with a common goal of delivering high-quality affordable housing, catalyzing economic development, and driving social impact strategies to deliver superior financial returns. Team Oski said that the HUD Innovation in Affordable Housing competition allowed them to cross-pollinate perspectives on how to address a historically underserved community. In doing so, the team cultivated an intimate understanding of the site-specific challenges and opportunities innate to the Atlanta Civic Center site. The jurors commented that Team

Oski's solutions were multifaceted, with multiple co-benefits. For example, their proposal included a green solution that not only addresses environmental concerns and benefits but also social concerns and financial restrictions.

In addition, HUD would like to acknowledge and commend all the student teams who participated in the 2022 IAH Student Design and Planning Competition. Although only four teams were selected as finalists, six additional teams submitted plans considered to be outstanding and that jurors ranked among the top 10 proposals. Those student teams are as follows, in chronological order by assigned team number:

- Team #253—Team Urban Innovators from Columbia University (Tamin Abedin, Kourosh Fathi, Eryn Halvey, Kamu Kakizaki, and Nicolas Nefiodow): The Urban Innovators Team proposed development taps into Atlanta's rich culture of music, civic engagement, and hip-hop to create a space where people can live affordably, invest in their talents, and connect deeply with their community. The team proposed to preserve the rich cultural history of the site by retaining and refurbishing the Civic Center and the Exhibition Hall. Their plan for the Civic Center was to wrap it in an open and transparent "sleeve" that would house new studios and small performance spaces for local talent. Jurors said the project was innovative, thoughtful, culturally sensitive, and equitable. They noted that the team clearly considered the history of the area while developing their plans. In addition, they used creative partnerships to achieve their goals, thus increasing the feasibility of their financial proposal.
- Team #262—Team Nip It in the HUD from the University of Michigan (Isabelle Borie, David Elam, Nathanael Nelson, Nelius Wanjohi, and Lauren Ashley Week): The "Nip It in the HUD" team presented Buttermilk Heights, a mixed-use, mixed-income community, anchored by a skilled trades incubator and training center. The design of their complex is drawn from footprints of houses on the site in the 1930s to encourage the site designers and visitors to address the site's legacy. The footprints are consolidated and abstracted in key places throughout the design to account for the needs of current and future generations. In the design plans, the Civic Center and Expo Hall buildings are preserved, with new cultural center buildings wrapping the public corners of the original structures, hiding the windowless 1960s facades, and providing opportunities for murals and other storytelling devices. The materials of the apartment units are reminiscent of Atlanta vernacular construction, with fiber-cement cladding, wooden porches, and traditional "haint" blue paint, creating a unique yet storied environment. Jurors said that the scale of the project integrates well with the scale of existing neighborhood development. Jurors also noted that the proposal preserves the Civic Center and Expo Hall while adding new cultural center buildings and is creative and practical.
- Team #267—Team Synthesis from Virginia Tech (Gabriela Borowiec, Makenzi Moore, Elizabeth Quill, and Chiravi Patel): The site proposed by Team Synthesis incorporated 240 units, 60 studios, and 90 one- and two-bedroom apartments in more than 280,000 square feet of new mixed-use development within four distinct quadrants to address community and residential needs. To ease integration into the community, the site plan differentiates the quadrants on the basis of the needs of residents and visitors to ensure a natural spatial flow, easy navigation, and privacy for residents while still meeting the commercial, civic, and

transportation needs of the greater neighborhood. The structures in the site plan demonstrate innovation focused on seamless growth and sustainability efforts using cross-laminated timber as the primary building material and through the modular design of the buildings. According to the team, the modular design allows for a minimization of preconstruction and labor costs while allowing for cheaper growth over time. That configuration enables the spaces to change and grow with the community without having to completely reconstruct frameworks. Juror comments stated that the proposal was thoughtful, centered around community needs and co-creation, and provides innovative solutions, particularly from an adaptability perspective.

- Team #270—Team U Mish from the University of Michigan (Clayton Artz, Anthony Bui, Kassem Chammout, Chelsea Gaylord, and Jihwan Park): Team U Mish proposed a mixed-use development called "The Buttermilk District" and said that it was where the history of place could be seamlessly integrated with the demands of building toward the future. The development was funded through a mix of debt, equity, and grant opportunities that include 9 percent Low Income Housing Tax Credits, tax exempt bonds, developer equity, a construction loan, and renewable energy and philanthropic funds. In addition, the team proposed partnering with the Southface Institute, Georgia Power, Georgia Tech, the YMCA, and Atlanta Workforce Development to provide successful delivery of services to create a vibrant, connected community. Team U Mish stated that the Buttermilk District was centered on delivering a connected community, where residents of diverse income levels are integrated, celebrated, and uplifted and where history and art meet to tell the stories of our past and work to build a brighter future. Jurors stated that the proposal thought outside the box on several fronts: financing, programming, resident participation, and site density in particular. Jurors also stated that the programming around financial rebuilding and employment were strong elements and very commendable.

- Team #271—Team Buff Goldy from the University of Minnesota Twin Cities and the University of Buffalo (Emily Anderson, Dakota Crowell, Lindsay Erdmann, Tia Jacobs, and Connor McManus): Team Buff Goldy's proposed development, titled "Heart of Atlanta," creates more than 1,000 new housing units, 40 percent of which are permanently affordable at 60 percent AMI or below; 138,000 square feet of leasable commercial, office, and active use space; a new 300-key hotel; a new 51,000-square-foot exhibition hall; and just over 6 acres of public park space. The proposed park space doubles as stormwater management infrastructure and includes a recessed playground designed to hold water during a "100-year storm." All buildings have green roofs to ensure a holistic approach to sustainability and climate resiliency. In addition, the policies, programs, and financial layering proposed for the site address past injustices based on race and income that includes a local, blended-subsidy approach to provide deeply affordable public housing units on site. Buff Goldy's site design maintains the existing historic Civic Center but includes a new, relocated Exhibition Hall that the team stated would help to open up the site while still ensuring state-of-the-art creative space around a renovated plaza. Jurors stated that the adaptation of the Exhibition Hall was well thought out and work well in the overall design of the site. Jurors also remarked that the innovative use of rooftops and additional greenspace also work well together. In addition, jurors said the proposed Anti-Displacement Preference and Right to Return policies to redress racial and economic injustices are important tools for the project.

- Team #275—Team Possibilities from the Georgia Institute of Technology and the University of Michigan (Keith Luu, Ashley Martinez, Sneha Moorthy, and Siddharth Sivakumar): For their proposal, Team Possibilities sought to reinvent the meaning of "civic center" and reunite the communities between historic Old Fourth Ward and Peachtree Street by repurposing the Boisfeuillet Jones Atlanta Civic Center site into a mixed-income-community living, working, and gathering space. A major aspect of the site design calls for leveraging the green public spaces to connect to surrounding neighborhoods and flow from the northeast corner to Peachtree Street. The team also proposed to connect the East Beltline from Ponce City Market to Central Park and toward the proposed I-85 Stitch, thereby connecting the Beltline to the inner city. Team Possibilities said that their goal for the site was to create housing that would enable residents to build a prosperous future and to allow residents to see their home as either a stepping-stone or a long-term sustainable option they could be proud of. Jurors commented that the emphasis on green space and public space—particularly introducing a link to the Beltline—was excellent, stating, "The project is thoughtful and feasible in terms of social justice, Atlanta history, and larger site-related strategies, particularly around Black-owned businesses."

All of this year's team proposals collectively rose to the challenge by considering the history of Buttermilk Bottom, using creative partnerships, innovative financial proposals, Anti-Displacement Preference, and Right to Return policies to address racial, density, and economic injustices in their designs.

HUD greatly appreciates the 2022 Innovative Affordable Housing jury members' dedication and hours devoted to the award selection process, all of the student teams and faculty advisors who participated this year, HUD staff and leadership for their support, and Atlanta Housing Authority for their involvement and partnership. Finally, HUD thanks Schatz Publishing Group, LLC, for planning and logistical efforts under the constraints of the COVID-19 pandemic. Their hard work and flexibility made this year's competition a success.

Author

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Post-Script

This competition is thoroughly documented on the web.

To learn more about the competition visit https://www.huduser.gov/portal/challenge/home.html.

For questions regarding the competition, please email IAH@huduser.gov.

Impact

A regulatory impact analysis must accompany every economically significant federal rule or regulation. The Office of Policy Development and Research performs this analysis for all U.S. Department of Housing and Urban Development rules. An impact analysis is a forecast of the annual benefits and costs accruing to all parties, including the taxpayers, from a given regulation. Modeling these benefits and costs involves use of past research findings, application of economic principles, empirical investigation, and professional judgment.

Increased 40-Year Term for Loan Modifications

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The views expressed in this article are those of the author and do not represent the official positions or policies of the Office of Policy Development and Research, the U.S. Department of Housing and Urban Development, or the U.S. Government.

Summary of Rule and Analysis

On April 1, 2022, the U.S. Department of Housing and Urban Development (HUD) proposed a rule to allow lenders to extend the repayment period of a mortgage loan to 40 years. HUD's current regulations allow mortgagees to modify a Federal Housing Administration (FHA)-insured mortgage by extending the total unpaid loan for a term limited to 30 years after a borrower's default. The loan modification is intended to assist borrowers with FHA-insured mortgages who are experiencing financial hardship due to negative life events or economic conditions and whose existing mortgages are in default or imminent default. Being able to offer a longer-term loan eases the burden of loss mitigation on lenders and FHA, and it prevents default, foreclosure, or other negative outcomes for certain borrowers who would not be able to retain their homes without an immediate reduction of their periodic mortgage payment.

A loan modification is a change to one or more terms of a borrower's loan to help cure the default, generally by reducing the monthly payment to a more affordable level. A loan modification typically involves extending the number of months to repay the loan, reducing the interest rate, adding missed payments to the principal, forbearing or reducing the principal balance, or some combination of those options. The 40-year repayment period would provide an additional option for a loan modification that could be used independently or combined with other options to assist FHA-insured borrowers at risk of default.

The 40-year mortgage remains rare but has become more commonly recognized in the mortgage industry. The Federal National Mortgage Association (Fannie Mae) and the Federal Home Loan Mortgage Corporation (Freddie Mac) provide a 40-year mortgage loan modification option.[1] The National Credit Union Association (NCUA) also allows for 40-year mortgages, and the U.S. Department of Agriculture (USDA) allows for loan modification up to 40 years if certain conditions are met beyond the requirements for a 30-year loan modification. An FHA Mortgagee Letter (ML 2022-07) established the 40-year loan modification as part of the COVID-19 Recovery Loss Mitigation Options but only under very specific conditions. By allowing 40-year loan modifications more generally, HUD would align with the government-sponsored enterprises (GSEs; Fannie Mae and Freddie Mac), NCUA, and USDA, ensuring that borrowers with FHA-insured mortgages receive equivalent options for home retention.

An advantage to the lender of extending the loan term is that it does not necessarily reduce the income from mortgage payments. The mortgage payments are calculated such that the net present value (NPV) of a stream of scheduled mortgage payments is equal to the principal. Extending the loan compares favorably with other methods, such as interest rate buydowns or principal reductions, both of which lower the NPV of mortgage loan payments.

The success of the 40-year loan modification will depend upon how it is combined with other loan modification policies and the prevailing market conditions. The aggregate impact will similarly depend upon the accessibility of the loan modification to borrowers. FHA encourages lenders to modify the loans if feasible. For a loan modification to be a preferred solution for both lenders and borrowers, the outcome for both must be better than that of a foreclosure, which involves costs to FHA, the lender, and the borrower. The estimated net quantifiable benefits of the modification range from approximately $84 million to $550 million in a given year, whereas transfers range from $87 million to $780 million. Some of the costs and benefits to lenders and borrowers and the transfers are likely to occur in the first year of the loan modification, whereas other effects will be periodic until the property is sold or the mortgage is fully paid.

Evidence of Success of Loan Modification Strategies

Loan modifications became a significant component of government intervention during the Great Recession. Modification programs to reduce foreclosures included the Home Affordable

[1] For information on trends in the use of different types of loan modification, see FHFA (2021). Over the last 10 years, the fraction of loan modifications by FNMA and Freddie Mac that "extend the term only" has increased to include approximately two-thirds of their loan modifications.

Modification Program (HAMP)[2] and loan modifications by GSEs. Effective policy design became a critical issue: Should the government assist borrowers by reducing the loan principal or subsidizing the payment? The right answer depends on borrowers' motivations.[3] Up to 70 percent default on their mortgages because they suffered a significant negative economic shock resulting in the inability to pay. Some choose to default once their home has become a depreciating financial asset. If negative equity is a primary motivator, then principal reduction would be more effective. Although some theoretical and empirical studies on the performance of modified loans have shown that principal reduction is the optimal type of modification due to its dual effect on payment burden and negative equity for the borrowers,[4] it is also the costliest option for lenders and, thus, the least used option.

To be considered effective, a loan modification should assist borrowers in continuing their scheduled payments long after modification.[5] Industry experience and empirical evidence[6] on loan modification programs during the Great Recession have determined that reducing monthly payments by 20 to 30 percent is the most cost-effective long-term modification strategy for borrowers, lenders, investors, and communities. Modifications that reduce mortgage payments by at least 10 percent consistently result in lower redefault rates than modifications that reduce payments by less than 10 percent (U.S. Treasury, FHFA, and HUD, 2016). Other research on the success rate of loan modification has suggested that the probability of re-default depends on several factors: the type and timing of modification, the characteristics of the borrower, and whether the loan is securitized.[7] Ganong and Noel (2020) found that modifications involving payment reductions are far more cost-effective than a principal reduction in preventing defaults. Agarwal et al. (2011) found that significant reductions in mortgage payments are associated with lower re-default rates. An analysis of GSE-backed mortgages using either HAMP or GSE loan modification programs during the Great Recession found that a 1-percent mortgage payment reduction reduced default rates in the 2 years after modification by 0.26 percentage point on average (Farrell et al., 2017). However, no consensus exists on the effect of extending loan duration on re-default. Voicu et al. (2012) found a positive correlation, whereas Agarwal et al. (2011) found a negative correlation.

FHA Loss Mitigation Program

The FHA Loss Mitigation Program, established in 1996, offers a comprehensive approach to promoting alternatives to foreclosure, enhancing lender flexibility to meet that goal, and reducing

[2] In 2009, the U.S. Department of the Treasury rolled out the federal government's foreclosure prevention initiative, the Making Home Affordable (MHA) program, which included the Home Affordable Modification Program (HAMP).

[3] For a comprehensive review of this literature, see Ganong and Noel, 2020.

[4] Das and Meadows (2013) find that reducing the principal amount is the optimal type of loan modification. Quercia and Ding (2009) and Haughwout, Okah, and Tracy (2016) confirm Das and Meadows' findings, but their small samples have limited statistical power because principal forbearance is relatively rare.

[5] Earlier performance of loan modifications in 2008 shows that within 6 months, more than one-half of all modified loans were 30 days or more delinquent, and more than one-third were 60 days or more delinquent (OCC and OTS, 2008, in Quercia and Ding, 2009).

[6] See An et al. (2021) for the list of studies supporting this finding.

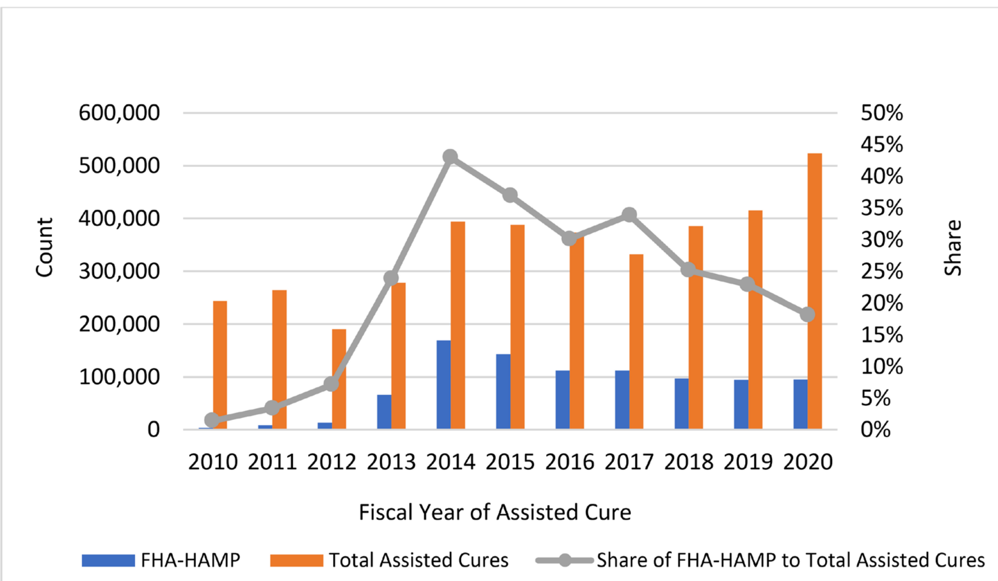
[7] See Le (2016).

losses to FHA's Mutual Mortgage Insurance (MMI) Fund.[8] Current loss mitigation options for borrowers whose mortgages are in default or imminent default include home retention options (e.g., informal and formal forbearances, Special Forbearance [SFB]-unemployment, and FHA-HAMP) and home disposition options (e.g., pre-foreclosure sales [PFS] and deed-in-lieu [DIL]). Home disposition options are available immediately upon default if the cause of the default is incurable—i.e., the borrower has no realistic opportunity to replace the lost income or reduce expenses sufficiently to meet the mortgage obligation. FHA's first objective is to help the homeowner remain in the home whenever possible; however, the home disposition options allow the disposition of the property without the full adverse impact of foreclosure.

Since FHA-HAMP was introduced in 2009 in response to the Great Recession, the use of that option has significantly increased. Exhibit 1 shows the number of cured defaults using FHA-HAMP between FY 2010 and FY 2020, which may include standalone loan modification, standalone partial claim, or a combination of loan modification and partial claim. FHA-HAMP gained traction starting in FY 2013 and peaked in FY 2014. FHA-HAMP has declined since then as the housing market has improved and delinquencies have fallen. In FY 2020, FHA-insured mortgages with assisted cures totaled 523,574, and FHA-HAMP represented 18 percent of all cures.

Exhibit 1

Total Assisted Cures and Total Cures by FHA-HAMP



FHA = Federal Housing Administration. HAMP = Home Affordable Modification Program.
Source: HUD/FHA

[8] The FHA Loss Mitigation Program replaced FHA's Mortgage Assignment Program effective April 26, 1996. See Mortgagee Letter 1996-24 (Termination of the Mortgage Assignment Program), Mortgagee Letter 1996-32 (Loss Mitigation – Mortgage Modification), and Mortgagee Letter 1996-61 (FHA Loss Mitigation Procedures).

Impacts on FHA

FHA's MMI Fund receives positive cash flows from mortgage insurance premiums (MIPs) paid by FHA-insured borrowers. The MMI Fund experiences outflows for loss mitigation efforts and claims paid to lenders for mortgages that have defaulted. Borrowers pay an upfront MIP of 1.75 percent of the loan value and an annual MIP of 0.80 percent of the loan value for loans with an initial loan-to-value ratio of 95 percent or less.[9] The MMI Fund is typically estimated to generate a negative credit subsidy in the year that loans are insured, which means that it provides an offsetting receipt for the federal government and does not need appropriations to cover the expected costs of insuring loans. Loans are valued based on their estimated NPV lifetime costs in the year they are insured.

FY 2020 witnessed positive loan performance until the onset of the COVID-19 crisis in March 2020. Although the share of loans originated with higher risk attributes declined in FY 2020, the overall portfolio performance worsened as early payment defaults increased from 1 to 3 percent, and seriously delinquent mortgages increased from 4 to 12 percent (FHA, 2021b).

As shown in exhibit 2, the bulk of total claims paid (by number) was for conveyance, or transfer of ownership to FHA; for claims from loss mitigation, partial claims made up by far the highest share. Compared with the average amount of a claim from conveyance, which was $144,000, the average claim from loss mitigation through partial claim was significantly lower, at $29,000.[10] Claims from loss mitigation accounted for a majority of the increase in the total claim amount. Before FY 2021, the share of total claims paid for loss mitigation was consistently lower than that of claims paid for the disposition of assets. However, in FY 2021, the share of loss mitigation claims reached 82 percent of total claims.

Exhibit 2

FHA Single-Family Insurance: Total Claims Paid by Claim Type (in million $)

	FY 2017	FY 2018	FY 2019	FY 2020	FY 2021
Loss Mitigation Claims					
Special Forbearance	0.97	1.03	1.19	0.94	0.03
Loan Modification	77	71	71	74	30
Partial Claim	1,747	1,477	1,769	1,993	5,333
Total	**1,826**	**1,550**	**1,841**	**2,068**	**5,363**
Home Disposition Claims					
Conveyance or Deed-in-lieu (DIL)	4,653	3,144	2,286	1,965	527
Without Conveyance	2,347	2,455	1,948	1,054	476
Pre-Foreclosure Sale (PFS)	601	384	257	205	171
Total	**7,600**	**5,983**	**4,491**	**3,224**	**1,174**
Grand Total	**9,426**	**7,532**	**6,332**	**5,291**	**6,537**
Loss Mitigation Claims (% share)	19	21	29	39	82
Home Disposition Claims (% share)	81	79	71	61	18

FHA = Federal Housing Administration. FY = fiscal year.
Source: U.S. Department of Housing and Urban Development/National Servicing Center

[9] For loans with an initial loan-to-value ratio of more than 95 percent, the MIP is 0.85 percent of the loan value.

[10] This amount is computed by dividing the total amount paid by the total number of claims.

Gains to FHA of the 40-Year Repayment Period

FHA incurs a loss from a mortgage claim event, and the loss amount depends on many factors, including the disposition channel. Foreclosed properties generally have higher severity compared with PFSs. When an FHA-endorsed mortgage terminates as a claim, the property is conveyed to FHA, and FHA makes a payment to the lender to settle the claim and acquire the underlying property (i.e., the underlying property becomes real estate owned, or REO). The net loss to the MMI Fund is the difference between the acquisition cost to HUD and recoveries realized by FHA on properties owned.

The acquisition cost, which is the claim payment FHA makes to the servicer, consists of the outstanding unpaid principal balance on the mortgage, foregone interest advanced by the servicer as a result of the mortgage default, and foreclosure expenses (e.g., legal and administrative costs paid by the servicer, including any expenses incurred in repairing or maintaining the property before conveyance). Each component is affected by several factors—for example, note rate and length of default-to-claim lag, use of judicial foreclosure process, borrower's financial condition, house price appreciation, and prevailing housing market conditions. Following acquisition, some properties are sold at a reduced price. For those properties that are not yet sold, FHA incurs holding costs associated with maintenance, repairs, tax payments, and other expenses related to preparing the property for sale. Upon sale of a property, FHA receives the sales price less any sales expenses.

Since the peak of $129,000 in FY 2012 (in nominal $), the average net loss decreased to $74,000 by FY 2021 (except for a slight increase in FY 2020).[11] The authors estimate that the average net loss to FHA from a foreclosure could range from $32,000 to $111,000 (2021$) per property, depending on economic conditions.[12] Using this range, the authors estimate that the annual total prevented net loss to FHA from foreclosures if distressed borrowers have the option of modifying their loans to 40 years could be between $237 million and $833 million.[13]

The reduction in losses to FHA can be considered a transfer that arises in the year the default is prevented by the 40-year loan modification. Alternative methods of expressing the impact could be to spread the costs avoided over the maximum life of a loan or the expected life of a loan.

Costs to FHA of 40-Year Repayment Period

The cost to FHA of helping a borrower cure a default by extending the repayment period is small compared with the interest expense, legal fees, and property management costs associated with foreclosure (see exhibit 2). Similarly, FHA would incur no incremental administrative cost in offering a 40-year versus a 30-year mortgage.

[11] This amount is the average net loss for the combined foreclosure (REO and TPS, or third-party sale) and PFS claims (see FHA, 2021b).

[12] The low estimate was the average net loss for 2017–2021, whereas the high estimate was the average for 2008–2011.

[13] This figure is estimated by multiplying the range by 7,500. The authors estimated a total of 7,500 borrowers could be prevented from ending in foreclosure or termination claim if the 40-year modification were an available option to them. See the computation of 7,500 mortgages in the following discussion.

Impacts on Lenders

A lender could face both gains and losses from a requirement to offer an extension of the loan repayment period. If the net effect of a loan modification on the value of the mortgage is positive, then the lender would incur no compliance cost. The loan modification would have been pursued regardless of any requirement by FHA. If, however, the lender incurs net costs for modifying a loan, then an incentive may be required for the lender to pursue a loan modification that generates benefits for other parties.

Considerations for All Types of Loan Modification

The gains of a loan modification to an FHA-insured lender are not as obvious as they would be to FHA, which guarantees the loss, or to the borrower, who could lose their home. For lenders, a loan modification can represent as much of an administrative burden as a foreclosure.[14] The lender will choose the least costly alternative (HUD, 2009).

Costs to FHA-insured Lenders of Loan Modification. The primary source of income for servicers is the monthly servicing fee, which is a fixed percentage of the loan's unpaid principal balance. In the case of default, the servicer can recover foreclosure costs but not modification costs. Offering loss mitigation options to borrowers can be costly and is not covered by insurance claims to FHA. In addition, the labor and overhead costs (e.g., staffing, physical infrastructure, and out-of-pocket expenses such as credit reports and financing costs) associated with modifications are not billable to investors (Cordell et al., 2009; Eggert, 2007).[15]

An additional cost of a loan modification is the repurchase of a loan once it is securitized. The cost to modify a loan will thus depend on whether a lender holds the mortgages on their balance sheets or with the servicers on behalf of mortgage-backed securities (MBS) investors in the case of securitized mortgages.[16] Although most FHA-insured mortgages are in mortgage pools held in the Government National Mortgage Association's (Ginnie Mae's) loan pools, loan modification requires that servicers purchase loans from those pools with their own funds and re-pool them after modification.[17]

Unlike modifications of conventional loans, this repurchase requirement applies to almost all FHA-insured mortgages. Beyond the direct costs of repurchasing a loan, executing a loan modification

[14] A lender would be more willing to incur costs to modify a loan for loans that are not fully insured. The loss of income from default is likely to outweigh any costs of loss mitigation. This kind of moral hazard has been empirically detected by comparing the performance of FHA and non-FHA loans (Park, 2016).

[15] In recent years, the Mortgage Bankers Association (in Goodman, McCargo, et al., 2018, and Fratantoni, 2020) has estimated that the per-loan cost of servicing a nonperforming loan is approximately $2,000.

[16] This section uses "lender" and "servicer" interchangeably. Although FHA-approved lenders may service their own mortgages or may subcontract out the servicing of their mortgages, they are responsible for all servicing actions, including the acts of their servicers, in line with FHA regulations. See FHA Single Family Handbook 4000.1, Section III.

[17] The repurchase decision is related because servicers are responsible for forwarding monthly payments to Ginnie Mae investors even when borrowers have failed to make those payments. Although HUD generally only reimburses lenders for missed payments at a debenture rate (the interest rate used by HUD to reimburse lenders for missed interest payments) and not the note rate (the interest rate paid by the borrower on the mortgage), lenders will lose the difference in those interest rates if they continue to forward the payments. Regarding re-pooling, achieving a sufficient volume to form a new pool is a challenge to servicers (see HUD, 2000).

incurs other risks. Because the process of purchasing and re-pooling could take several months, servicers are exposed to the risk that interest rates will change before the loan can be re-pooled, which could result in a loss for the servicers. The risk of loss from an interest rate increase could dampen the willingness to offer loan modifications (HUD, 2016, 2000).

Gains to Lenders of Avoiding a Foreclosure. FHA limits what it will reimburse an insured lender on a claim, which provides some motivation to avoid foreclosure. HUD may require the lender to repair a property before conveyance. When a borrower defaults, the disinvestment in property can be significant.[18] Depending on the type of damage to the property, the charges may or may not be reimbursable.[19]

Lenders bear some foreclosure costs. FHA limits the reimbursement of foreclosure costs to two-thirds of approved foreclosure costs. Some types of foreclosure costs are partially or fully reimbursable, whereas others are not reimbursable at all.[20] The loss in income to lenders from not receiving interest payments is limited by HUD's "debenture interest rates," which are typically lower than the prevailing market rate.[21] The estimates of interest costs of a foreclosure are approximately 10 percent of the unpaid balance.[22] The FHA-insured lender would bear a fraction of that cost depending on the difference between the loan rate and HUD's debenture rate. Whether the loss in interest income from a foreclosure is greater than the loss in income from modifying the loan depends on the duration of the two processes.

FHA offers servicers incentive payments[23] for the successful completion of the approved loss mitigation options and, at the same time, imposes financial penalties for failing to engage in loss mitigation and adhere to FHA's loss mitigation guidelines.[24] A HUD report (2000) found that incentive payments do not cover the full costs associated with using each loss mitigation option, especially regarding payment for loan modifications.[25] The compensation structure of servicers does not cover the extra modification costs.

[18] Stress discounts—or the reduction in property value of a foreclosed home—can vary between 3 and 9 percent or be up to 27 to 30 percent for houses with low-priced characteristics in low-priced neighborhoods (Campbell, Giglio, and Pathak, 2009) and during economic events such as the Great Recession (Madar, Been, and Armstrong, 2008; UBS, 2008; White, 2009).

[19] Only surchargeable damage to a property caused by fire, flood, earthquake, hurricane, tornado, boiler explosion (for condominiums only), or mortgagee neglect is not reimbursable. In cases of nonsurchargeable damage that occurs during the time of the mortgagee's possession, HUD may require the mortgagee to repair such damage before conveyance, and HUD will reimburse the mortgagee for reasonable payments, less any insurance recovery.

[20] For instance, attorney fees are limited to 75 percent of the maximum attorney fee for incurred fees associated with a routine foreclosure that was not completed because any of the following occurred after the mortgagee-initiated foreclosure: the borrower filed for a bankruptcy petition; the borrower executed a DIL of foreclosure; or the borrower successfully completed a PFS.

[21] See https://www.hud.gov/program_offices/housing/comp/debnrate.

[22] See HUD (2010) for a discussion of the estimates of the transaction costs of a foreclosure.

[23] Current incentive payments include $100–$200 for SFB-Unemployment; $500 for an FHA-HAMP Partial Claim; $750 for an FHA-HAMP Loan Modification, plus up to $250 for reimbursement of title search, endorsement of the title policy, and recording fees; $1,000 for PFS; and $250 for DIL. Additional incentive payments are offered to servicers on the basis of their performance. See FHA Single Family Handbook 4000.1.

[24] See 24 C.F.R. § 203.500 *et seq.* and 24 C.F.R. 30.35(c) (2).

[25] The report also mentioned that the maximum reimbursement of $250 for title search costs was inadequate in many cases.

Interest Costs of Extending the Loan Repayment Period

Extending the repayment period of a fixed-rate mortgage could affect the market value of other terms of the loan, such as the interest rate, so that a lender is indifferent between a 30-year and 40-year repayment period.[26] Extending the repayment period could expose the lender (or investor) to greater risk in the performance of the loan (either prepayment or default) or interest rate risk (the opportunity cost of funds for the lender). A lender could pass the costs of managing the risk of a longer repayment period onto the borrower, making it less advantageous. If, instead, the interest rate is restricted to that of a 30-year loan, then a lender could be less willing to offer the loan modification. Establishing a reference interest rate is necessary when evaluating whether extending the repayment period puts any burden on lenders.

Effect on Default Risk. The immediate (conditional) risk of default would be diminished by extending the repayment period and thus issuing a mortgage with more affordable payments. This short-run reduction of default risk from an income shock to the borrower could be partly offset by a stronger incentive for strategic default later on. A 40-year repayment period could discourage the borrower from building equity after having survived the initial serious delinquency. A longer term in which to repay potentially presents a greater probability that the owner will find themselves underwater at some point in the future. However, given that liquidity constraints have been shown to be a greater motivator for default than negative equity, the prospect of redefault should not raise the interest rate.

Effect on Prepayment Risk. The typical life span of a mortgage is less than 10 years, well under the agreed-upon repayment period of either a 30- or 40-year loan. Prepayment behavior could be different with a longer-term loan, although the direction is difficult to determine, just as for default. On the one hand, the lower periodic mortgage payment of a 40-year loan would reduce the urgency of refinancing, making prepayment less likely. On the other hand, the prospect of greater long-run interest costs of a longer-term loan could hasten the decision to refinance and prepay.

Effect on Interest Rate Risk. Even if a loan continues to generate income, lenders of fixed-rate mortgages face interest rate risk (Fuster and Vickery, 2015; Hoffman et al., 2019). An anticipated increase in current interest rates reduces the expected value of a mortgage's revenue stream. If banks lend long-term and borrow short-term, then the financing costs of borrowing could exceed the revenue received from mortgage payments. The reverse is also true: if interest rates fall, then the value of the mortgage would increase. Aversion to this type of risk makes longer-term loans costlier. The ability of financial institutions to handle this interest rate risk varies.[27]

[26] Informal evidence shows that there could be a difference. Freddie Mac's Primary Mortgage Market Survey shows that the rate for a 30-year FRM has never been lower than that for a 15-year mortgage; the median difference is 50 basis points. A reliable comparison between 30- and 40-year rates is more difficult because survey data on loans with a 40-year term are not as prevalent. Ganong and Noel (2020) estimate a difference of 32 basis points between 40- and 30-year rates.

[27] Banks with longer maturity liabilities retain more mortgages; banks with shorter maturity liabilities transfer interest rate risk by securitizing more loans (Xiao, 2021).

Liquidity Costs of Extending the Loan Repayment Period

The secondary market for 40-year loans may not be as advanced as for standard 30-year loans. Goodman, Kaul, et al. (2018) estimate that the rate on mortgage-backed securities composed of 40-year loans is 50 basis points higher than that of MBS of comparable 30-year loans. If additional cost arises from the secondary market being less competitive, then this difference can be expected to fall as investors become more familiar with the 40-year loan. Any remaining difference in interest rates would be due to the slight but potential interest rate risk of holding a 40-year loan.

Opinions differ on how quickly the secondary market will develop.[28] Ginnie Mae announced the creation of a new pool type to support the securitization of modified loans with terms up to 40 years.[29] That action will allow Ginnie Mae issuers to offer loan modifications that carry a lower monthly payment than that for a 30-year term while retaining the ability to securitize the loans for sale in the secondary market.

Impacts on Borrowers

A 40-year modification may be a solution for borrowers who defaulted earlier in the life of the loan, have accumulated more arrearages, or face higher interest rates at the time of modification. The immediate benefit to the seriously delinquent borrower would be to ameliorate the financial distress that would cause foreclosure. If prevailing interest rates have increased since a loan was originated, then lengthening the repayment could either partially or completely offset the increase in mortgage payments of a modified loan at a higher rate (Goodman, Kaul, et al., 2018).[30]

Extending the repayment period will reduce a borrower's periodic mortgage payment by distributing the payments over more years. The level of reduction of mortgage payments achieved by extending the repayment period has limitations. The reduction of the mortgage payment attainable through extension diminishes as interest rates are higher because the interest that accumulates over a longer repayment period adds to the cost of the loan. Accumulated arrearages limit the effectiveness of repayment extensions to reduce the mortgage payments below the initial loan payment.

The additional interest cost will vary with the borrower's time value of money, as expressed by a discount rate (the rate at which the consumer discounts future consumption relative to the present). If the discount rate and interest rate are equivalent, then the present value of future

[28] Goodman, Kaul, et al. (2018) suspected that the secondary market would grow slowly if implemented but that "some subsidy will probably be needed to assure economic execution during the interim period" (p. 7). Bhagat and Stein (2021) are confident that FHA-insured 40-year loan modifications will find a market niche based on a comparison with similar pools of FHA-insured modified loans reinstated after undergoing loss mitigation. The experience of GSEs in securitizing their 40-year modified loans suggests that such custom pools that include 40-year loan modifications would be able to find sufficient liquidity.

[29] See Ginnie Mae, 2021.

[30] Guidance for loan modification requires that the refinance be offered at an interest no greater than the "market rate," which is often defined as no more than 25 basis points greater than the most recent Freddie Mac modification interest rate for a 30-year fixed rate mortgage, rounded to the nearest one-eighth of 1 percent (0.125 percent) as of the date the borrower is offered a permanent loan modification. See FHA Single Family Handbook 4000.1 Glossary.

mortgage payments is not affected by extending the repayment period of the loan.[31] Future interest will be discounted by the same rate at which it accumulates. A borrower with a higher discount rate than the interest rate would gain from the intemporal tradeoff of extending the repayment period. A borrower would gain as the loan balance accumulates at an interest rate less than the borrower's discount rate. Thus, borrowers with a lower discount rate are not likely to gain as much from extending the loan repayment period.[32] For those borrowers, the increase in interest payments over the course of the loan would outweigh the gains from reducing the periodic payment. However, HUD expects that the financial gains from avoiding a foreclosure could outweigh any loss from higher interest costs of the modified loan.

A borrower is not obligated to carry the loan for 40 years. The average life of an FHA-insured mortgage is 7 years. If a higher present value of mortgage payments incurs a financial burden, then, after the loan is cured and as soon as interest rates are favorable, a borrower would refinance into a less expensive loan. Similarly, if the financial situation of the borrower improves, they could choose to resume their previously scheduled payments, which would shorten the mortgage and reduce the higher interest costs of the 40-year modification (Bhagat and Stein, 2021). Alternatively, many borrowers are likely to move and sell their home before the end of their mortgage term and would, thus, not be subjected to the full costs of additional years of payments and interest made.

Value to Borrowers of Avoiding Foreclosure

The homeowner's benefit of avoiding foreclosure includes escaping various losses from foreclosure. Direct costs include moving costs, legal fees, tax penalties, and administrative charges to the borrower.[33] Other losses include the loss of equity (for loans with a loan-to-value ratio of less than one) and the option value of realizing future housing price appreciation (Eberly and Krishnamurthy, 2014). Even if a borrower is in a position of negative equity, the net value of the mortgaged home could be positive to the occupant if the borrower has developed a unique attachment to the structure or neighborhood.[34] All households need shelter regardless of the asset value of their residence. A lower credit rating stemming from a foreclosure would make finding alternative housing more expensive, regardless of tenure.[35]

Nonfinancial costs include emotional stress imposed on affected household members, financial instability, living in a neighborhood with a lower quality of life, physical health problems induced by the move, and even an increased likelihood of divorce. Diamond, Guren, and Tan (2020) stress

[31] If all borrowers were identical, then interest rates would equal borrowers' discount rates. However, several types of loans, borrowers, and housing markets exist. Gerardi, Shapiro, and Willen (2007) argue that housing finance decisions vary across households due to the heterogeneity of the cost of funds to borrowers.

[32] A borrower with a lower discount rate than the interest rate would not borrow unless they face temporary liquidity constraints, value the purchased item at more than the market price, expect asset price growth, or expect a future decline in interest rates so that they can refinance their loan.

[33] A previous analysis by HUD (2009) estimated those direct costs to be approximately $12,000 (2021$).

[34] Owners could also value a home at a higher value than a potential buyer simply because they have an aversion to loss (Tversky and Kahneman, 1991).

[35] Brevoort and Cooper (2013) find that credit scores decline into the subprime range as a borrower's mortgage enters foreclosure. However, Diamond, Guren, and Tan (2020) find that the impact on credit scores of a foreclosure is not significant because the primary reduction to the credit score results from serious delinquency, which has already occurred before the foreclosure.

the importance of accounting for such nonfinancial costs, especially for marginal homeowners on the brink of avoiding foreclosure.

The primary driver of default is a negative economic shock to a household from unemployment, illness, or divorce (Foote, Gerardi, and Willen, 2008). The loss of income and the inability to borrow at reasonable rates would force a borrower into an undesirable foreclosure. In some cases, a foreclosure could be preferable to a household if it is severely underwater. However, empirical work has shown that the market value of a home must be as low as 50 percent of the loan balance before becoming the primary cause of default (Bhutta, Dokko, and Shan, 2017).[36] A loan modification supported by FHA may be the only option for FHA-insured borrowers who are delinquent and struggling to remain in their homes due to financial hardship.

Demand for 40-Year Loan Modification by Borrowers

A modification that lowers monthly payments could be key to a borrower's ability to bring their mortgage current, prevent imminent re-default, and ultimately retain their home and build wealth through homeownership. The demand for the 40-year modification would be correlated with the number of borrowers who are seriously delinquent. The serious delinquency (SDQ)[37] rate rose from 4 percent at the end of April 2020 to 12 percent by the end of FY 2020, as the number of seriously delinquent borrowers grew from about 328,000 to approximately 926,000. That increase occurred because a substantial number of borrowers requested to defer their monthly loan payments under HUD's administrative authority to provide forbearance options that aligned with or exceeded those options under the Coronavirus Aid, Relief, and Economic Security (CARES) Act, as forbearance requests transitioned into serious delinquencies a few months later.

The number of participants in a 40-year loan modification would depend upon the characteristics of borrowers and lenders, the specifics of FHA policy, and market trends. The authors assume that FHA would require lenders to offer the 40-year refinancing on terms specified by a mortgagee letter or regulation. The longer repayment period could be a first, intermediate, last, or even only step of a loan modification plan. The relevant comparison is to the 30-year refinance.

To understand what drives demand by borrowers for a 40-year loan modification, the authors assume that the 30-year mortgage is an alternative modification offered by FHA. To ensure demand for a 40-year loan modification, it must improve a borrower's well-being by more than a 30-year extension. For example, the 40-year modification would be the choice of a borrower who needs greater liquidity and discounts the future at a higher rate.[38] The difference between the monthly payment provided under a 40-year loan modification and a 30-year loan modification may be

[36] If, instead, the monthly cost of owning is higher than the cost of renting, then providing an incentive to homeowners to remain in their homes (by providing lower mortgage payments at a level comparable to area rents) could benefit the public.

[37] The SDQ rate tracks the percentage of FHA-insured mortgages when the borrower is 90 or more days delinquent, including mortgages in foreclosure and bankruptcy.

[38] The present value is a more accurate measure of the burden to a consumer of a future stream of loan payments. The present value of additional interest payments depends on how borrowers discount the future, or how they value future consumption relative to the present. A 40-year extension would increase the total amount paid over the course of the loan because of the increase in interest. However, it could also result in smaller mortgage payments. A borrower who discounts the future more would be more likely to be interested in a 40-year extension because he or she would benefit from the smaller nearer-term payments and discount the longer-term payments.

significant for a borrower and their ability to afford the modified payment. The choice between a 40-year and 30-year mortgage can also be influenced if one entails higher administrative costs (such as having to prove the need for the 40-year loan term). HUD expects that the distribution of borrower and loan characteristics will be sufficient to generate a positive demand for the 40-year term extension.

For a borrower to agree to a 40-year loan modification, the modification must also be preferred to the alternatives, such as defaulting, selling the home, or self-curing. The 40-year loan modification is preferable to self-curing when the household is liquidity constrained and does not expect an imminent recovery; preferable to foreclosure when the costs of foreclosure and leaving the home are greater than the costs of remaining in the home with a loan modification; and preferable to selling when moving costs are higher than remaining in the home.

Available data on completed loan modifications show that 524,000 loan modifications were processed between FY 2012 and FY 2016. The authors use those data to estimate the potential number of loans that could be prevented from ending in foreclosures or with a termination claim paid by HUD by modifying the mortgages to 40 years. If borrowers receive a 16- to 26-percent payment reduction to the principal and interest portion of their monthly mortgage payments, 15.56 percent will end up in foreclosure or termination claim. However, if borrowers receive a payment reduction of 26 to 50 percent, that share decreases to 10.22 percent, for a difference of 5.34 percent of borrowers prevented from ending in foreclosure or termination claim.

Using the 90+ day FHA-defaulted portfolio as of the end of November 2021, the authors found two potential groups of seriously delinquent borrowers could have benefited from a 40-year loan modification. The first group is the 75,000 borrowers who were at risk because either their partial claim was already maxed out or the remaining amount of partial claims available to them was insufficient to cover their current delinquencies. Of those borrowers, if one assumes that 5.34 percent would not end up in foreclosure or termination claim if they obtained the 40-year modification, that would be 4,000 borrowers (75,000 x 0.053). Second, approximately 40,000 borrowers have interest rates that are already lower than the (then) Freddie Mac PMMS of 3.125 percent. If those borrowers were to need a loan modification, their payments would increase if they had to modify their mortgages to 30 years. However, if they could receive a 40-year term, then their payments would decrease an average of 14.4 percent, meaning that approximately 3,500 borrowers (40,000 x 0.087)[39] would have been prevented from ending in foreclosure or a termination claim.

In sum, of the current total number of 90+ day defaulted cases, 7,500 borrowers could potentially be prevented from ending in foreclosure or termination claim if the 40-year modification were an available option. That number of prevented foreclosures is a high estimate because it was based on FHA's defaulted portfolio as of November 2021, when many FHA-insured borrowers were financially affected by the COVID-19 pandemic. For the low estimate, the authors estimated that approximately 3,000 borrowers could have been prevented from ending in foreclosure or termination claim. As previously discussed, the nominal losses to a homeowner from a foreclosure

[39] Comparing the number of borrowers who could be prevented from ending in foreclosure or claim termination based on the reduction of payment shows an 8.7-percentage-point difference between those borrowers receiving a payment reduction of 1 percent or less (29.9 percent) and those receiving a 2- to 15-percent payment reduction (21.2 percent).

would be at least $12,000. If a 40-year modification were available to borrowers, the authors estimate that the total annual costs to borrowers that could be saved would be approximately $36 million to $90 million.

Whether demand for the 40-year loan modification exists among borrowers is not a sufficient criterion for success. The first and most desirable outcome for other stakeholders (FHA, lenders, and the general public) is when the 40-year extension prevents a default (40-Year > Default > 30-Year). Less desirable is when no efficiency gains are realized from the 40-year alternative but only a transfer to a borrower (40-Year > 30-Year > Default). For that reason, conditions can be placed on offering the 40-year option, such as a targeted payment reduction.

Social Benefits of Avoiding Foreclosure

Foreclosures create negative externalities that make them costly not just for foreclosed homeowners but also for society overall. The authors' current estimates of the external cost of a foreclosure range from $0 to $28,000, with $14,000 as a central estimate.

Exhibit 3

Estimates of Economic Externalities of Foreclosure

	Low Estimate	Middle Estimate	High Estimate
Externalities from Blight	$0	$10,000	$20,000
Local Government Costs	$0	$4,000	$8,000
Total	**$0**	**$14,000**	**$28,000**

Source: Estimates by the authors

Property Market Spillovers

Disinvestment will adversely affect occupied homes in addition to foreclosed ones. Multiple empirical studies have detected the negative effect on housing prices of a nearby foreclosure. Immergluck and Smith (2006) found an approximately 1-percent reduction in values of surrounding properties within one-eighth of a mile of a foreclosure.[40,41] Accurate estimation of such a foreclosure externality is difficult because of self-selection: homes that are foreclosed on are more likely to be in neighborhoods characterized by a weak housing market. According to Lee (2008), the sources of foreclosure spillovers are poor property maintenance causing worsening urban blight, lower property appraisals based on comparable properties, and an increase in the supply of vacant properties. A number of studies have attempted to separate the impacts of foreclosure, abandonment, and vacancy. Most conclude that the negative impact on surrounding prices of nearby properties is approximately 1 to 2 percentage points (Campbell, Giglio, and Pathak, 2009; Fisher, Lambie-Hanson, and Willen, 2015; Harding, Rosenblatt, and Yao, 2009; Zhang and Leonard, 2014). However, Geraldi et al. (2015) refute any significant impacts of foreclosures on neighboring home values by including the neighborhood level of serious delinquencies as a control.

[40] Given that 31.4 acres are in a radius of one-eighth of a mile and a reasonable density is three units per acre, HUD estimated that the impact on 94 properties was likely driven by neighborhood-wide market trends.

[41] A relevant finding of the Immergluck and Smith (2006) study was that the foreclosure of government-guaranteed loans seemed to have no measurable impact on sales prices.

For this analysis, HUD assumes that the price of surrounding properties is best approximated by the national average of the sales price of a home insured by FHA (approximately $250,000) and that the externality is a 1-percent decline in home value of the immediately surrounding properties. If an average of four properties suffers a decline in value, then the aggregate impact would be $10,000. If the property remains abandoned, the adverse hedonic impacts on neighborhood quality will linger. This wider and deeper impact could be twice as high, at $20,000, but would be expected only during a severe property downturn. The authors' low estimate is $0, reflecting empirical findings of no real effect.

Costs to Local Government of Foreclosure

The local government experiences losses from a foreclosure through unpaid property taxes on the foreclosed property, unpaid utility bills, property upkeep, policing, legal costs, building inspections, an increase in demand for social services, and, in some extreme cases, demolition of a building that has become a public nuisance. HUD adapted the median case for a property that is foreclosed on, sold at auction, and vacant for some time, for which occasional police intervention is required to secure the property. The estimate includes only direct costs to the jurisdiction of a foreclosure, which can be considered a deadweight loss of public resources. The costs to the local government would be approximately $6,200[42]; accounting for inflation, that amount would be $8,200 in 2021.[43]

External Costs of Displacement

The social costs associated with the disruption of housing tenure would merit greater policy flexibility during a crisis. Displacement of households from eviction during a pandemic could impose additional private and public costs. During a public health crisis, being forced to seek temporary housing solutions, such as public shelters or staying with family and friends, would lead to greater crowding and thus higher transmission rates of infectious disease. Avoiding overcrowding would represent an unambiguous gain for the affected households and the general public. One study of New York City during the COVID-19 pandemic estimated that a 10-percent increase in the number of occupants in a housing unit could lead to a 7-percent increase in hospitalizations (Clement, 2021).

Equity Impacts

The goal of FHA programs is to assist borrowers traditionally underserved by conventional markets. Those underserved borrowers—including qualified first-time, low- and moderate-income, and minority homebuyers—are expected to have fewer resources to respond to a financial setback, more difficulty recovering from such a setback, and a greater possibility of foreclosure. In FY 2021, the composition of borrowers served by FHA-insured mortgages was 32 percent minority (Native

[42] See Apgar et al. (2005), scenario 4a/4b.

[43] Another estimate is from the Office of the State Comptroller of New York (2016). which published the results of a survey of local governments showing that the average annual maintenance costs resulting from a foreclosure were approximately $1,200 (2021$).

American, Asian, Black, or Hispanic); 44 percent White; and 24 percent not reported.[44] Home Mortgage Disclosure Act (HMDA) data from 2020 show that FHA's share of lending to Black (17 percent) and Hispanic households (25 percent) is higher compared with the rest of the housing market (6 percent for Black and 10 percent for Hispanic households) (FHA, 2021a). For first-time homebuyers, FHA reached record highs in insurance endorsements in FY 2021 in terms of both share (85 percent) and volume ($176 billion in unpaid principal balance). FHA's share of lending to first-time homebuyers was almost 40 percentage points higher than that of the rest of the housing market.

FHA data show that minority borrowers presently make up a larger share of the seriously defaulted cases than their share of the active portfolio. Their seriously defaulted rate is also higher than for White borrowers or borrowers who did not disclose their race. First-time homebuyers also presently make up a larger share of the seriously defaulted cases than their share of the active portfolio. Among minority borrowers, Black borrowers appear to be significantly more affected. Specifically, first-time homebuyers who are Black seem disproportionately affected, with a higher percentage of the seriously defaulted portfolio and a much higher seriously defaulted rate.

Because minority and first-time homebuyers constitute the majority of those individuals with FHA-insured mortgages, extending the repayment period could provide additional flexibility to prevent defaults and retain homeownership and wealth for those underserved households.

Homeownership and Wealth Creation

Low-income and minority borrowers (controlling for other factors such as income and credit score) were disproportionately affected by foreclosures during the Great Recession (Bocian et al., 2008; Kermani and Wong, 2021) and, recently, by the COVID-19 pandemic[45] (see, e.g., An et al., 2021; Chakrabarti and Nober, 2020; van Dorn, Cooney, and Sabin, 2020). A study by Kermani and Wong (2021) of racial differences in property appreciation shows that most of the disparity between Black- and White-owned properties (on average, 3.7 percent per year) stems from distressed sales, either through a short sale to a third party or foreclosure to the lender. Homeownership must be sustainable for a family to build wealth.

Disparities in Loan Modification

The loan modification policy is intended to promote equity by preserving the housing wealth of lower-income households. However, unfair practices have been identified throughout the housing market and even within institutions designed to promote fair housing (Oliver and Shapiro, 2006). The implementation of loan modification policy must be applied fairly to achieve the higher goal of wealth equity. Findings concerning loan modification terms and subsequent loan performance by race and ethnicity vary. Some studies find no evidence of racial disparities in the incidence of loan modifications (Been et al., 2013; Collins, Reid, and Urban, 2015; Collins and Reid, 2010) or find that race, ethnicity, gender, and income have "very little" impact on borrowers' successful

[44] Declaration of race and ethnicity is voluntary for borrowers. FHA's share of nonrespondents increased from 17.30 percent in FY 2020 to 24.32 percent in FY 2021.

[45] An et al. (2021) find that "between April 2020 and December 2020, minority and lower-income borrowers had twice the nonpayment rates of White and higher-income borrowers. Even after controlling for conventional risk factors, Black borrowers have about 40 percent higher rates of nonpayment, the lowest-income borrowers around 80 percent higher" (p. 2).

participation in HAMP (Mayer and Piven, 2012). Other studies find that neighborhoods with large shares of Black residents are more likely to receive modifications (Been et al., 2013; Chan et al., 2014) and that some differences are present in the incidence of HAMP modifications across protected classes, but those disparities stem from differences in servicers' determination of borrowers' eligibility (GAO, 2014). Evidence supports that the 40-year term would be implemented fairly to advance the economic interests of all protected classes.

Summary of Economic Impacts

A cost-benefit analysis of the incremental impact of the 40-year loan modification is difficult without more information concerning the context and method of implementation.[46] The contribution of a repayment extension, and thus its incremental impact, will depend on the design of the loan modification.[47] Increasing the repayment period could be the first, final, intermediate, or only step of a loan modification. How the repayment period is used in conjunction with other term modifications should affect the incremental impact of the 40-year opportunity. The sequence of the 40-year loan modification could determine both the number and types of loans modified. External market factors will also play a role in determining the incremental impact of this policy. Whether the allowed modification can achieve the target reduction of monthly mortgage payments will depend on the terms of the original loan, its evolution, and economy-wide interest rates at the time of modification.

Exhibit 4 summarizes the economic impacts of an increased 40-year term for loan modifications. Assumptions concerning economic trends and details of the loan modification policy would be necessary to provide more reliable estimates for many of the impacts outlined in exhibit 4. Whether FHA chooses to use the term extension as a standard practice or to reserve the option for national crises will also determine its regulatory impact.

Once it occurs, the cost of a foreclosure becomes a burden to FHA, the lender, and the borrower and could cause social externalities. The loss of a foreclosure to FHA-insured lenders includes the unreimbursed costs of a default. The loss to FHA will be the largest because FHA insures the lender against default. The payment of the claim is essentially a transfer from the taxpayer. The gains to FHA can be passed on to the U.S. Treasury or other participants of FHA's programs in the form of lower mortgage insurance premiums. More information on economic conditions, which affect loss severity and recidivism, would allow one to calculate those gains to FHA more precisely.

[46] One of the most complete studies of loan modification policy found term extensions to be a Pareto optimal loan modification strategy for borrowers, lenders, and the government (Ganong and Noel, 2020).

[47] How a loan is modified could determine whether there is a reduction of mortgage payments. For example, extending the loan term, reducing the interest rate or the mortgage's outstanding balance, or a combination of those practices can lower monthly payments. In contrast, adding delinquent payments to the unpaid principal balance can result in higher monthly payments (Cordell et al., 2009; White, 2008).

Exhibit 4

Summary of Economic Impacts

	Gains	Losses	Net Impact
FHA	Reduces expected claim expenses and net loss from foreclosures	• *Could lower value of modified loans because of longer maturity or a lower coupon* • *Incentive payments to lenders* • *In cases where not effective, it possibly increases the cost of claim from greater depreciation*	Expected Positive Net Cash Flow
Borrower	Relief allows household to sustain homeownership and avoid costs of foreclosure (financial and nonfinancial costs).	*Higher interest payments over life of loan and thus slower equity buildup*	Expected Positive (if negative, then borrowers would refuse)
Lender	Avoidance of costs of processing foreclosure[48]	• *Out-of-pocket costs in modifying loans not covered by FHA insurance claims* • *Interest rate risk from repurchase and re-pooling of loans, or longer repayment period* • *Loss of income if debenture rate is lower than market rate* • *Administrative cost of modification* • *Avoided stress discount from sale of foreclosed properties* • *Potential loss in liquidity from re-pooling of loans indirectly affecting financial markets*	Net impact depends on whether there is any risk to extending the term of the loan.
External Effects	Avoidance of costs of foreclosure to public	*N/A*	Positive
Equity Considerations	Enhancing mission of FHA to increase access to homeownership, especially to underserved communities, through greater flexibility	*N/A*	Most likely positive

N/A = not applicable.

The gain to a borrower from avoiding a foreclosure is at least $12,000. This estimate includes some of the more easily identifiable transaction costs of foreclosure. Other costs, or "frictions," of foreclosure are potentially more significant to homeowners. Precise estimates of those extra costs do not exist but likely vary by the availability of alternative housing and the underlying cause of a foreclosure. Eligible borrowers who would not have defaulted without the loan modification gain by reducing the NPV of their loan payments. Such gains occur regardless of the impact on the probability of default.

[48] The term extension should not reduce income from mortgage payments. The cost of foreclosure is not included in the claim (property repair, legal fees, etc.).

The social costs of a foreclosure are more difficult to monetize. However, the external impacts of avoiding a foreclosure are always positive. External gains of avoiding foreclosures justify a loan modification policy even when internal gains and losses are equivalent.

Lenders bear the costs of modifying eligible loans. Depending on how the policy is implemented, administrative costs would be identical regardless of whether a loan term is 30 years or 40 years. Extending the repayment period could produce an incremental opportunity cost of funds to lenders. The conclusion of a benefit-cost analysis would depend on the amount of the cost and how much is passed on to borrowers in the loan modification.

If a lender can pass on the full cost of modifying the loan, then the NPV of the loan to the lender remains the same, but the payment reduction for the borrower declines. In this scenario, the negative impact on the probability of default would be weaker. If the lender were to bear the full cost of the term extension, then the NPV of the loan to the lender would decline. A rough estimate of the potential cost to lenders compares favorably to the upper range estimate of the gain to FHA.[49] In the case of the lower estimate of gain to FHA, expected gains of only 2 percent of the loan balance from borrowers, lenders, and the public combined would bring about net gains.

Focusing on the quantifiable costs and benefits of the proposed rule, exhibit 5 presents the authors' estimates of the net benefits of a 40-year loan modification for an average mortgage of $250,000 insured by FHA. The authors then multiply the per-loan cost, benefit, and transfer to the range of the estimated total number of mortgages (3,000 to 7,500) that could be prevented from ending in foreclosure or termination claim if the 40-year modification were an available option to those defaulted mortgages.

Exhibit 5

Estimated Annual Quantifiable Economic Impacts (1 of 2)

	Amount per Loan[a]		Total Costs, Benefits, and Transfers[b]	
	Low Value	High Value	Low Estimate	High Estimate
Costs				
Lenders				
Servicing a nonperforming loan	$500	$2,500	$1.5 million	$19 million
Borrowers				
Increased interest paid[c]	-$259	$359	-$780,000	$2.7 million
Total	**$241**	**$2,860**	**$723,000**	**$21.5 million**
Benefits				
Lenders				
Avoided loss of interest from foreclosure[d]	$11,500	$11,500	$34.5 million	$86 million
Avoided stress discount[e]	$7,500	$37,000	$22.5 million	$281 million

[49] For example, suppose that a lender is neutral between a 30-year loan at 5 percent and a 40-year loan at 5.25 percent. The annualized cost to the lender for extending the repayment period is 25 basis points. The NPV of this loan would fall by approximately 3 percent of the loan principal. This cost to lenders is less than if they were required to buy down the interest rate to reduce mortgage payments by 10 percent.

Exhibit 5

Estimated Annual Quantifiable Economic Impacts (2 of 2)

	Amount per Loan[a]		Total Costs, Benefits, and Transfers[b]	
	Low Value	**High Value**	**Low Estimate**	**High Estimate**
Borrowers				
Avoided foreclosure (loss of equity, cost of moving, loss of credit)	$12,000	$12,000	$36 million	$90 million
Local Government				
Avoided direct costs	$0	$8,200	$0	$61.5 million
Public				
Avoided price decline to neighbors	$0	$20,000	$0	$180 million
Total	**$31,000**	**$88,700**	**$93 million**	**$665 million**
Transfers				
FHA (to Treasury)				
Avoided net loss per foreclosure	$32,000	$111,000	$96 million	$833 million

Note: Totals may not add up due to rounding.

a. The estimates for costs, benefits, and transfers are calculated using the FHA average loan size of $250,000.

b. These estimates are computed by multiplying amount per loan by 3,000 (low estimate) or 7,500 (high estimate).

c. This amount depends on unpaid principal balance, interest rates of existing and modified loans, and borrower's discount rate. It is computed using a 5-percent interest rate and an average FHA unpaid principal balance of $115,000 to get the NPV of the difference in interest paid throughout the term between a 30-year and a 40-year term, annualized over 40 years. The annualized amount is a positive cost for consumers with low discount rates and negative for those with high discount rates. To simplify the analysis, the interest rate is assumed to be equal to the discount rate.

d. This amount is 10 percent of the unpaid balance.

e. This figure is 3 to 15 percent of home value, depending on the cause of discount (e.g., death or bankruptcy of seller) and housing market conditions, among others.

Conclusion

Allowing lenders to provide a 40-year loan modification would support HUD's mission of fostering homeownership by assisting more borrowers with retaining their homes after a default episode while mitigating losses to FHA's MMI Fund. HUD believes that, in some situations, a borrower seeks to engage in loss mitigation but is unable to provide loss mitigation to a degree sufficient to prevent default. In such cases, an additional 120 months on the length of the recast mortgage would allow for a lower monthly payment and additional opportunity to account for missed payments. Longer repayment periods allow the loan principal to be divided into smaller periodic repayments and thus pose less of an immediate burden to borrowers facing an unexpected loss of income. Compared with other types of loan modification, a term extension does not necessarily reduce the value of the loan to lenders. The largest gain from providing immediate liquidity would be to lower the probability of default and thus the expected costs of foreclosure to FHA, borrowers, lenders, and the general public. Lenders may incur costs, but the authors expect those losses to be outweighed by the gains of preventing defaults.

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What Happens When You Assume

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The views expressed in this article are those of the author and do not represent the official positions or policies of the Office of Policy Development and Research, the U.S. Department of Housing and Urban Development, or the U.S. Government.

Abstract

Mortgage assumption allows borrowers to transfer both their property and their mortgage to a homebuyer. Assumption of a loan has value when the note rate is below prevailing market rates. This paper uses survival analysis to estimate the likelihood of assumption and the effect of assumption on the likelihood of default. The author finds that every additional $1,000 in assumption value is associated with a nearly 2-percent increase in the likelihood of assumption. Assumption is more likely when the existing homeowner is seriously delinquent and when housing markets are weak. Assumption subsequently lowers by 20 to 40 percent the risk that a loan will default relative to loans that are not assumed. As mortgage rates rise from recent historic lows, mortgage assumption may become more common.

Introduction

When borrowers sell their homes, they usually use the proceeds to pay off the remaining balance of their mortgage. In fact, most loan contracts require such payment. But some mortgages, such as those insured by the federal government through the Federal Housing Administration (FHA), allow homebuyers to "assume" the debt of sellers. A homebuyer may be interested in the existing mortgage if the interest rate is lower than prevailing market rates or the terms of the contract are otherwise better.

The mortgage assumption value (MAV) is the difference between the unpaid balance and the present value of the remaining payments discounted at prevailing market interest rates. The assumption value increases with larger loan balances, more payments remaining, and higher spreads between the mortgage rate and prevailing market rates. However, declining interest rates over the past several decades have meant that the assumption option is rarely "in the money." The average rate on new 30-year fixed-rate mortgages fell below an unprecedented 2.7 percent in 2020, but nearly doubled to over 5 percent by early 2022. Rising mortgage rates may create value for borrowers with assumable loans.

This paper discusses the history and limited existing research on mortgage assumptions. Using a sample of more than 23,000 FHA-insured loans and a semi-parametric survival analysis model, the paper examines the financial and economic determinants of mortgage assumption and the average effect of mortgage assumption on loan performance. The author finds that the likelihood of assumption increases nearly 2 percent for every $1,000 increase in the assumption value. Assumption subsequently decreases the likelihood of default. These results are important for understanding the effect of interest rates on the housing market and evaluating FHA's financial risk.

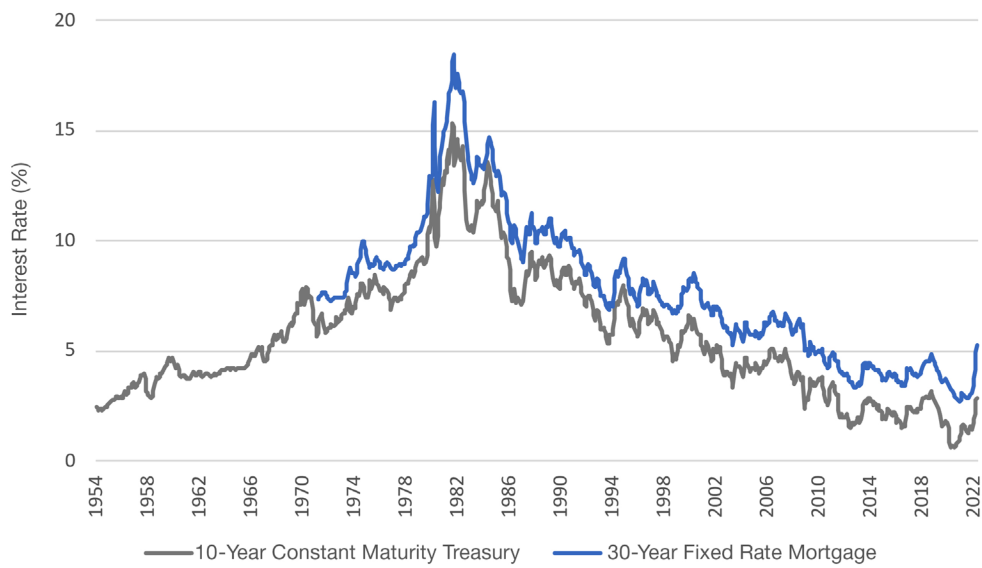
Assumptions and Due-on-Sale Clauses

Mortgage underwriting typically entails assessment by a lender of the borrower's collateral, creditworthiness, and capacity to repay. However, those assessments may be of limited use if the homeowner is able to convey the mortgage in a property transaction (Goddard, 1932). To protect their financial interests, lenders place contract provisions that prohibit assignment to a successor borrower without consent of the lender. Modern terminology labels these mortgage assignments as "assumptions" and restrictions on assignment as "due-on-sale" or similar clauses.

Due-on-sale clauses remained a relatively arcane part of mortgage lending until the 1960s, when interest rate risk, rather than credit risk, prompted lenders to enforce the provisions. Exhibit 1 shows the rate on 10-year constant maturity Treasury securities and the average interest rate on 30-year fixed-rate mortgages. Between 1960 and 1970, the 10-year Treasury yield approximately doubled, from 4 percent to 8 percent. Rates roughly doubled again over the following decade, peaking at 15.3 percent in mid-1981. Mortgage rates reached more than 18 percent at the same time. Consequently, homebuyers in the 1970s and 1980s faced dramatically higher interest rates on new loans than the rates sellers typically carried on their existing mortgages.

Exhibit 1

Historical Interest Rates



Sources: Board of Governors of the Federal Reserve System, Market Yield on U.S. Treasury Securities at 10-Year Constant Maturity, Quoted on an Investment Basis; Freddie Mac, 30-Year Fixed Rate Mortgage Average in the United States. Retrieved from FRED, Federal Reserve Bank of St. Louis

Simulations by Lacour-Little, Lin, and Yu (2020) demonstrated how assumability partially offsets the negative impact of rising interest rates on house prices. Sellers capitalize the value of below-market interest rates through higher sales prices. Sirmans, Smith, and Sirmans (1983) used a hedonic house price model and found that buyers assuming an existing mortgage paid roughly $3,000 more than comparable properties, meaning roughly one-third of the MAV is capitalized into the sales price. The MAV may not be fully capitalized for several reasons, including transaction costs, buyer's tax rate, expected length of tenure, and expected future interest rates (Agarwal and Philips, 1985; Allen and Springer, 1998; Ferreira and Sirmans, 1987; Lacour-Little, Lin, and Yu, 2020; Sirmans, Smith, and Sirmans, 1983). Sunderman, Cannady, and Colwell (1990) focused on the fact that the unpaid balance of a mortgage typically declines through amortization, whereas house prices typically (but not always) rise, meaning that the assumed loan often can finance only a portion of the sales price. The authors found that the capitalization rate declines as the loan-to-value (LTV) ratio increases.

Due-on-sale clauses prohibit assumptions, forcing buyers to shoulder higher debt payment burdens or sellers to lower asking prices. Bonanno (1972) argued, "Depressed conditions and excessive economic contractions created by high interest rates are rendered all the more severe by the artificial reduction in the transfers of real property induced by the discouragement of deals by buyer [sic] and sellers because the due-on-sale clause hangs over their heads like the sword of Damocles." The due-on-sale provision effectively serves as a prepayment penalty equal to the value of the mortgage assumption option (Dunn and Spatt, 1985). Several state courts ruled that due-on-sale clauses were unconscionable and a restraint on the alienation of property (Murdock, 1984). However, the Federal Home Loan Bank Board (FHLBB) preempted these state rules for federally chartered savings and loan associations in 1976, an action upheld by the U.S. Supreme Court.[1] Congress then extended the preemption to all mortgage lenders through the Garn-St. Germain Depository Institutions Act of 1982:[2]

> Notwithstanding any provision of the constitution or laws (including the judicial decisions) of any State to the contrary, a lender may … enter into or enforce a contract containing a due-on-sale clause with respect to a real property loan … [T]he exercise by the lender of its option pursuant to such a clause shall be exclusively governed by the terms of the loan contract, and all rights and remedies of the lender and the borrower shall be fixed and governed by the contract.[3]

After the Garn-St. Germain Act, due-on-sale clauses became standard for most conventional mortgages. By contrast, federal agencies that provide mortgage insurance continue to allow assumption by creditworthy borrowers. More important, however, declining mortgage interest rates since the mid-1980s largely removed the financial incentive for assumptions.

Little theoretical or empirical research on the determinants and effects of mortgage assumptions has been done due to their general scarcity in the mortgage market. Assumption is typically presumed not to be an option. For example, Kau and Kennan (1995) distinguished between endogenous, or "optimal," prepayment based on the incentive for a borrower to refinance if prevailing rates are less than the coupon rate and exogenous prepayment arising from personal circumstances, which "most commonly involves the sale of a house with a nonassumable mortgage for such reasons as job relocation or change in family size" (Kau and Kennan, 1995: 226). Assumability would enable property transactions without prepayment; therefore, prepayment would always be optimal, in theory, with perfectly rational borrowers. Meador (1984) used the different rules governing state- and federally chartered institutions in California before the Garn-St. Germain Act as a natural experiment. He found that repayment rates fell 0.52 percentage points for every percentage-point increase in mortgage rate spread for institutions preempted by FHLBB but 1.21 percentage points among institutions subject to the decision of the California Supreme Court. The lower repayment rates contributed to disproportionate financial losses among state-chartered institutions.

The effect of assumption on default is more ambiguous. Deng, Quigley, and Van Order (2000) noted, "A borrower forced to move (e.g., due to divorce or job loss) who cannot have the mortgage assumed has a very short remaining term and may thus default with little negative equity" (Deng,

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[1] *Fidelity Federal Savings and Loan v. Reginald de la Cuesta*, 458 US 141 (1982).

[2] Public Law 97-320, October 15, 1982.

[3] Section 431(d) provides certain exceptions to this preemption, including subordinate liens and transfers relating to death or divorce. Further, Section 431(c) states that assumptions are not prohibited and lenders are in fact encouraged to offer interest rates below market.

> In the exercise of its option under a due-on-sale clause, a lender is encouraged to permit an assumption of a real property loan at the existing contract rate or at a rate that is at or below the average between the contract and market rates, and nothing in this section shall be interpreted to prohibit any such assumption. Nevertheless, few conventional lenders appear to be swayed by this "encouragement clause."

Quigley, and Van Order, 2000: 280). This argument suggests that the assumption option may lower the risk of default. On the other hand, the continuation of a loan that would have been paid in full prolongs exposure to an adverse income or house price shock. Assumptions may also be used to circumvent mortgage underwriting—the original concern of lenders to include due-on-sale provisions in loan contracts. Allen and Springer (1998) noted that the mortgage assumption value is not limited to the interest rate environment but also includes transaction cost differentials and qualification criteria and that these considerations may even outweigh interest costs.

A HUD task force in the 1980s investigating fraud and abuse in FHA's mortgage insurance program found losses associated with the free assumption of FHA-insured loans, including "straw buyers" qualifying for FHA insurance before flipping the property to less creditworthy borrowers. To curb those abuses, FHA implemented a policy of assessing the creditworthiness of homebuyers seeking to assume an FHA-insured loan (HUD, 1986, 1988). According to the Department of Housing and Urban Development Reform Act of 1989,[4] "The Secretary shall take appropriate actions to reduce losses under the single-family insurance programs," including "requiring that at least one person acquiring ownership of a one- to four-family residential property encumbered by a mortgage insured under this subchapter be determined to be creditworthy under standards prescribed by the Secretary, whether or not such person assumes personal liability under the mortgage." Further, the successor borrower must intend to occupy the property as a principal residence or approved second home and not an investment property (HUD, 1989). Those reforms drastically curtailed assumptions. However, FHA-insured assumptions must be manually underwritten, whereas most new endorsements are evaluated by the Technology Open to Approved Lenders (TOTAL) mortgage scorecard, an empirically derived algorithm that assesses credit risk.[5]

Assumptions in the 21st Century

Continuing a decades-long trend, mortgage interest rates generally fell over the past two decades, from a high of more than 7 percent to less than 3.5 percent in 2012. However, rates rebounded to nearly 5 percent by 2018 such that more than three out of four existing 30-year fixed-rate home mortgages insured by FHA had below-market rates (exhibit 2). Given the remaining mortgage payments, this interest rate difference translates into an average MAV of $11,200, or a median of $9,244 (exhibit 3).[6] The aggregate MAV was more than $81 billion, or roughly $1,050 for every owner-occupied housing unit in the United States, and 0.33 percent of the aggregate value of the housing stock.[7]

[4] Public Law 101-235, December 15, 1989.

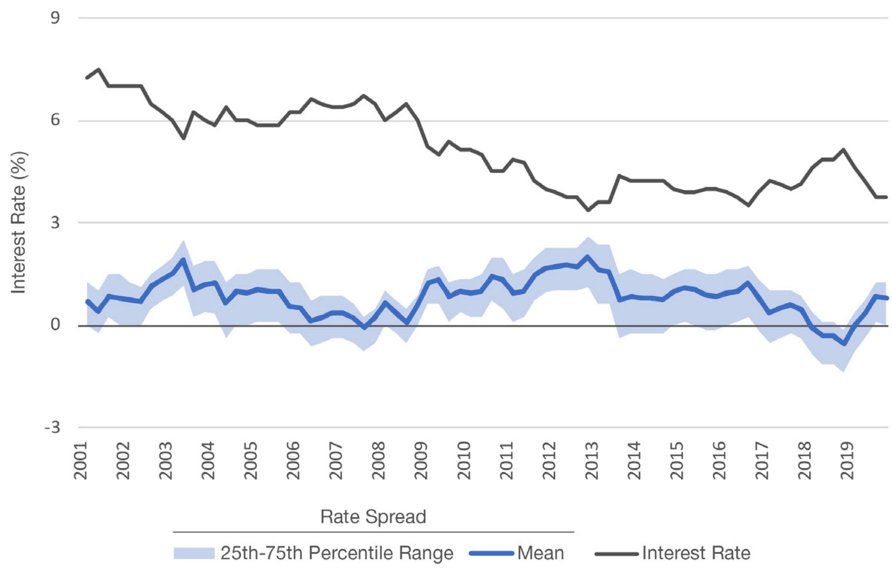
[5] For mortgage assumptions, see Sections II(A)(8)(n) and III(A)(3)(b) of the FHA Single Family Housing Policy Handbook. For underwriting using the TOTAL mortgage scorecard, see Section II(A)(4). https://www.hud.gov/sites/dfiles/OCHCO/documents/4000.1hsgh_Update7.5.pdf.

[6] Among loans with below-market rates, the average is $16,156 ($13,314 median).

[7] Based on 2018 American Community Survey one-year estimates of owner-occupied housing stock and aggregate value.

Exhibit 2

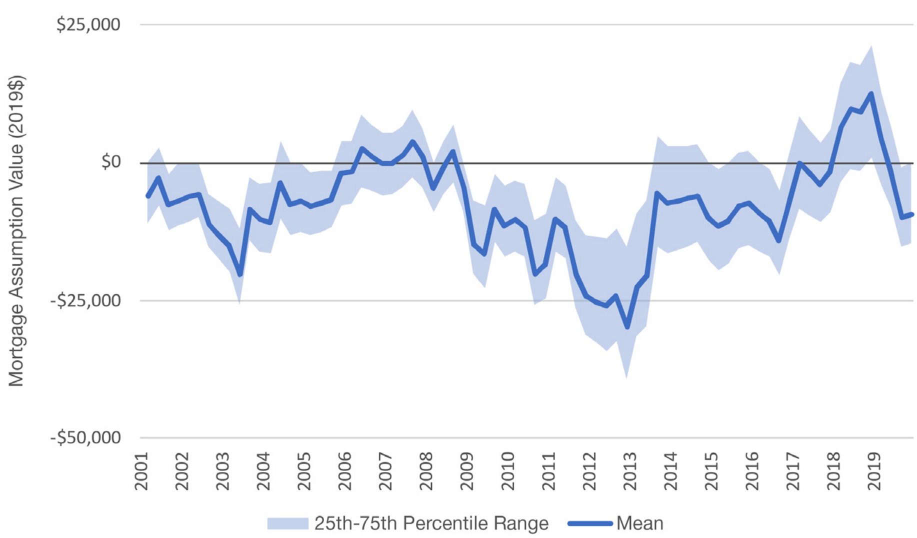
Interest Rates and Rate Spreads



Source: Author's tabulations of Federal Housing Administration administrative data

Exhibit 3

Mortgage Assumption Value

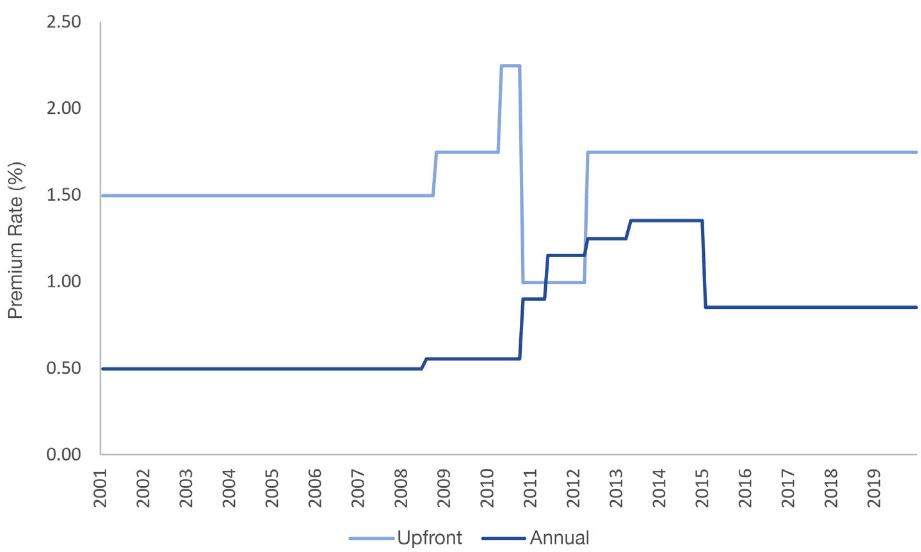


Source: Author's tabulations of Federal Housing Administration administrative data

Insurance premiums below current rates have values similar to below-market interest rates. In 1998, Congress passed the Homeowner Protection Act to automatically terminate private mortgage insurance once the balance of a mortgage reaches 78 percent of the original value of the collateral.[8] Because private mortgage insurance typically covers only the top 20 to 30 percent of the original mortgage, continued insurance after amortization had reduced the unpaid balance was considered excessive.[9] FHA implemented a comparable policy for loans closed on or after January 1, 2001 (HUD, 2000a, 2000b). The new policy canceled the collection of annual insurance premiums even though FHA insurance continues to cover the full loan amount for the life of the loan. However, faced with mounting credit losses during the Great Recession, FHA rescinded the premium cancellation policy and raised insurance premiums. For most 30-year fixed-rate loans, upfront mortgage insurance premiums increased from 1.5 percent to 2.25 percent and are currently 1.75 percent (exhibit 4). Annual premiums rose from 0.5 percent to 1.35 percent and are now 0.85 percent. Further, annual premiums are required for the life of the loan for most applications received on or after June 3, 2013 (HUD, 2013). Lower premiums and premium cancellation effectively lower monthly mortgage costs similar to below-market interest rates.

Exhibit 4

FHA Mortgage Insurance Premiums



Source: Author's tabulations of Federal Housing Administration administrative data

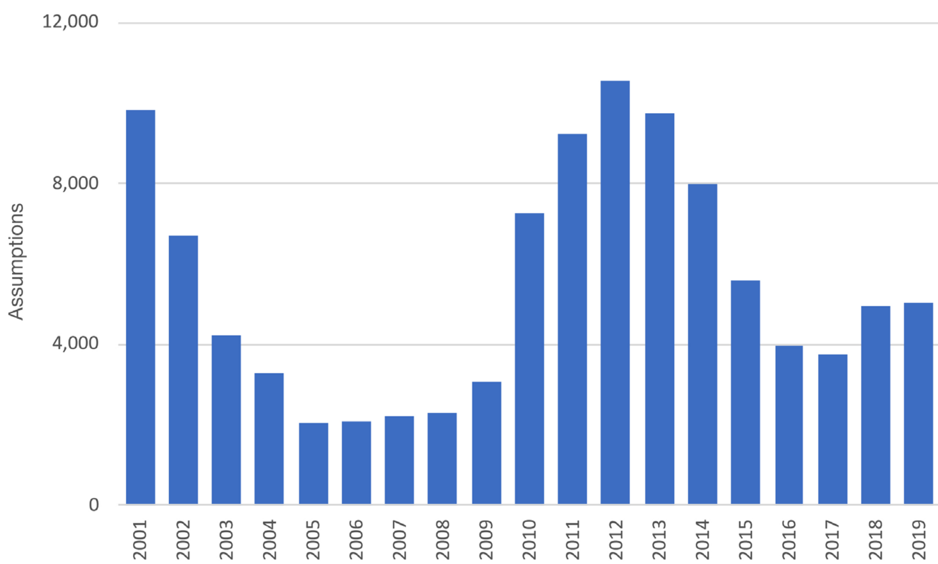
Nearly 104,000 FHA-insured loans were assumed between 2001 and 2019, from a low of barely 2,000 in 2005 to more than 10,500 in 2012 (exhibit 5). However, fewer active FHA-insured loans existed before the Great Recession. As a share of active loans, the assumption rate fell from 0.27 percent in early 2001 to just 0.05 percent in early 2006 (exhibit 6A). Although the absolute number of assumptions rose again in the early 2010s, the assumption rate was much lower than in 2001.

[8] Public Law 105-55, July 29, 1998.

[9] Senate Report 105-129 (1997).

Exhibit 5

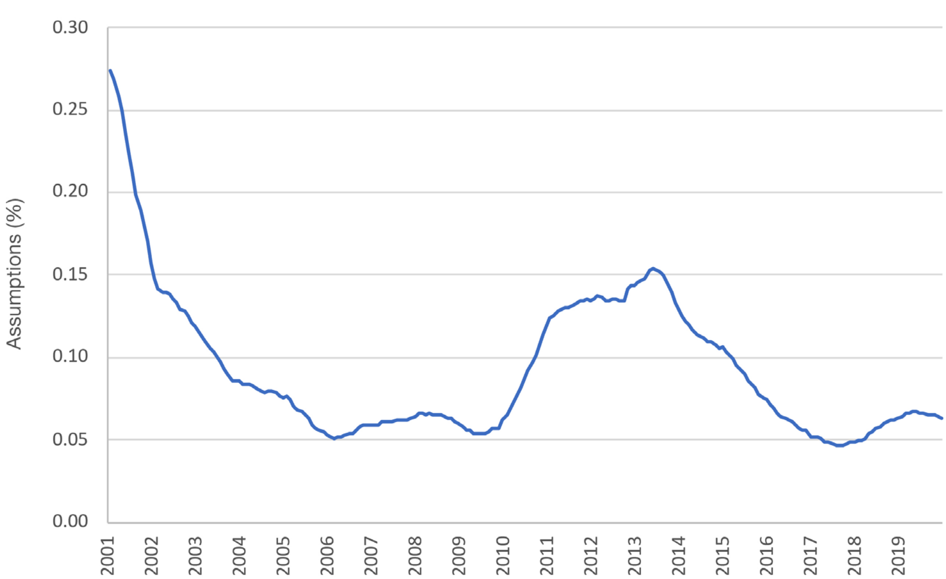
Assumptions



Source: Author's tabulations of Federal Housing Administration administrative data

Exhibit 6A

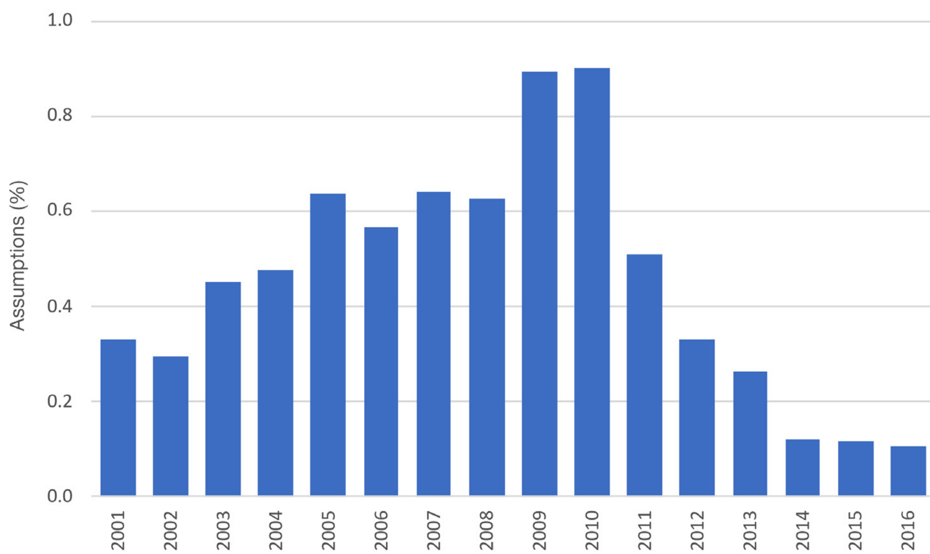
Assumption Rate—Rate Among All Active Loans



Source: Author's tabulations of Federal Housing Administration administrative data

Exhibit 6B

Assumption Rate—Rate by Cohort

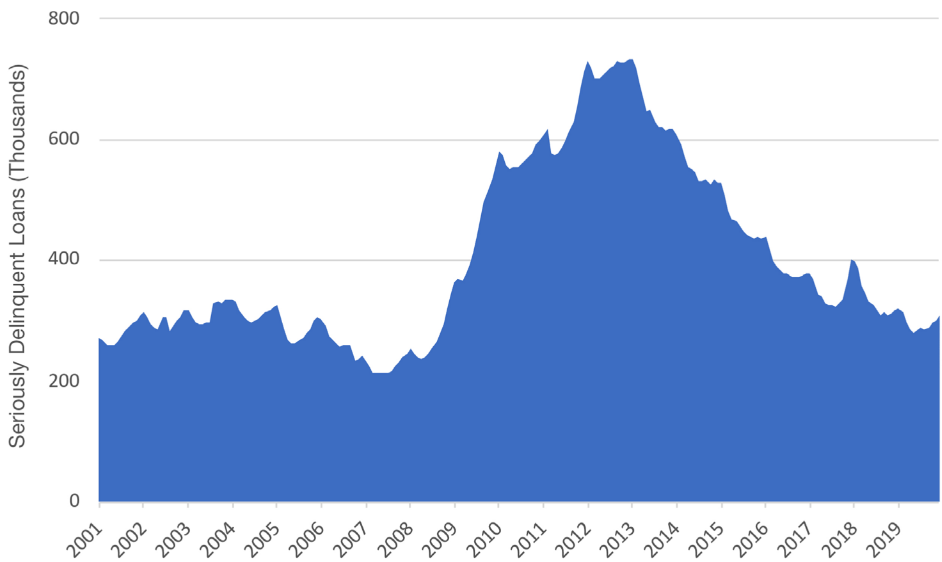


Source: Author's tabulations of Federal Housing Administration administrative data

The increase in assumptions when the financial value of assumption was extremely low is unexpected. However, the aftermath of the Great Recession also experienced tighter underwriting standards and a reduction in credit availability. Assumptions may have enabled marginal homebuyers to access mortgage credit through existing loans. "One motivation for an above-market assumption is the buyer's ability to avoid the loan qualification process involved with new loans. The qualification process can involve significant origination costs and subject the borrower to stringent qualification criteria that can preclude the borrower from obtaining a new loan" (Allen and Springer, 1998: 268). In addition, the housing bust created a large stock of delinquent borrowers looking to sell in any way possible (exhibit 7). Mortgage assumption may be an alternative to default and foreclosure if a willing buyer can be found.

Exhibit 7

Delinquent Loans



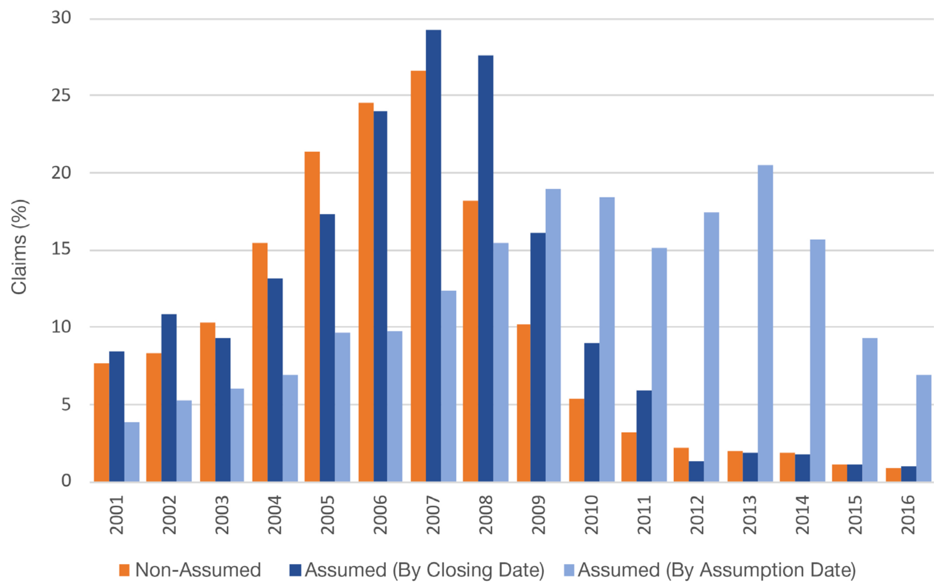
Source: Author's tabulations of Federal Housing Administration administrative data

Exhibit 6B shows the assumption rate by cohort between 2001 and 2016. Roughly one of every 214 FHA-insured loans originated between 2001 and 2019 has been assumed, but the rate tripled from 0.3 percent among loans originated in 2002 to nearly 0.9 percent for loans originated in 2009 and 2010. The rate declines for more recent vintages with less seasoning (i.e., less time exposed to be assumed).

A higher share of assumed loans has resulted in FHA mortgage insurance claims. Exhibit 8 shows the claim rate by cohort and assumption status. Roughly 8 percent of loans closed between 2001 and 2016 and never assumed have terminated with an insurance claim. By comparison, 13 percent of assumed loans have gone to claim.

Exhibit 8

Mortgage Insurance Claims by Assumption Status



Source: Author's tabulations of Federal Housing Administration administrative data

Data and Methodology

This paper uses administrative data from FHA's 203(b) mortgage insurance program to examine the causes and consequences of assumption. The data are restricted to 30-year fixed-rate mortgages for the purchase of existing single-family homes with loan-to-value (LTV) higher than 95 percent that were active between 2001 and 2019.[10] That sampling frame yielded a dataset of more than 23,400 loans, including all assumed loans, 1-in-50 never-assumed loans that defaulted with an insurance claim, and 1-in-1,000 other non-assumed loans. Weighting was used to account for oversampling of assumptions and claims. Exhibit 9 provides descriptive statistics. Due to generally falling interest rates and, thus, positive rate spreads, active loans in the sample had an average mortgage assumption value of *negative* $7,962 over the study period. By contrast, because the upfront mortgage insurance premium had already been paid (or financed) on existing loans but would be required on originations, the premium assumption value averaged $6,703. Overall, the total assumption value averaged negative $1,259; however, assumption values varied substantially both across borrowers and across time.

[10] Loans were also restricted to less than $625,500. FHA mortgage insurance premiums have minimal variation by credit risk but differ by *LTV* ratio, loan term, and loan amount. Those data restrictions create a standard FHA mortgage insurance premium within a given time period.

Exhibit 9

Descriptive Statistics

	Mean	Standard Deviation		
		Overall	Between	Within
Assumption Value	-$1,259	17,337	14,172	10,356
Mortgage Assumption Value	-$7,962	17,303	14,239	9,820
Premium Assumption Value	$6,703	8,034	6,092	4,831
Loan-to-Value Ratio	86%	17	12	11
Delinquency				
Currently Delinquent	0.15	0.36	0.23	0.28
Months Delinquent	1.49	5.77	3.03	4.43
Ever Delinquent	0.32	0.47	0.34	0.29
Delinquency Episodes	0.97	2.13	1.25	1.35
Economic Conditions				
Unemployment Rate	6.4%	2.7	2.4	1.6
Change in Employment	1.0%	2.5	1.9	2.0
Delinquency Rate	4.7%	3.5	3.3	2.1
Change in House Values	2.6%	6.9	6.3	5.2
Value Ratio	104.0%	113.5	63.4	94.9
Number of Home Sales	1,573	1,985	2,008	503

Notes: Sample includes 23,407 subjects with average 58.3 months for 1,365,044 observations. Unweighted statistics.
Source: Author's tabulations of FHA administrative data

Survival analysis helps address the issues of censoring and differences in exposure. This article uses semi-parametric survival analysis to model the assumption hazard

$$h(t) = h_0(t)e^{\beta X_t + \delta AV_t + \phi + \theta}$$

where h_0 is an unspecified baseline hazard. Loans that terminate without assumption are right-censored. In addition, the study period ends in 2019 to avoid complications related to the COVID-19 pandemic. The author used a Cox proportional hazard model rather than a subdistribution model because he is interested in the cause-specific effect of the assumption value on the likelihood of assumption (Allison, 2018; Austin, Lee, and Fine, 2016). However, he also estimated a Fine-Gray subhazard model that treats loan termination as a competing risk to find the effect of assumption value on the cumulative incidence of assumption.

The coefficient of interest δ captures the increase in assumption hazard associated with the estimated assumption value. The assumption value is separated into two measures: the mortgage assumption value (MAV) and the premium assumption value (PAV). Both measures are adjusted for inflation using the chained consumer price index from the Bureau of Labor Statistics.

The author estimated MAV as the difference between the face value of the remaining mortgage amount and its market value after discounting the payment stream by current market interest rates.

$$MAV_t = UPB_t - NPV_{rt}(PI)$$

where

UPB_t is the unpaid principal balance in month t, including upfront mortgage insurance premium if financed, which is equal to the net present value of PI discounted at the original mortgage interest rate (i)

PI is the fully amortizing payment of principal and interest based on the original principal balance (OPB) and mortgage rate

$$PI = OPB \times \left(\frac{i}{1-(1+i)^{-360}}\right)$$

and NPV_{rt} is the net present value discounted by the current market mortgage interest rate (r)

$$NPV_{rt}(PI) = \sum_{t=1}^{T} \frac{PI}{(1+r)^t}$$

The stream of mortgage payments becomes more heavily discounted as prevailing mortgage rates rise, lowering the net present value and increasing the assumption value.

PAV is the difference between the net present value of the premium schedule on new originations and the net present value of the existing premium schedule, both discounted using current mortgage rates.

$$PAV_t = NPV_{r\hat{t}}(MIP_t) - NPV_{r\hat{t}}(MIP)$$

where MIP_t is the mortgage insurance payment at the current premium rate, including new upfront mortgage insurance premiums; MIP is the mortgage insurance payment on the existing loan (in which the upfront premium is already paid or financed into the loan amount[11]); and $\hat{t}$ is the length of time over which premiums are collected. FHA loans with case numbers before June 2013 could have their insurance premiums canceled once the unpaid principal balance fell to less than 78 percent of the property value at origination. For computing the NPV of MIP_t before June 2013, the author used 78 percent of the property value at time t.

Fixed effects capture time-invariant impacts of state ϕ and performance year θ. Covariates X account for changing economic conditions and borrower status.

LTV Ratio	The contemporaneous *LTV* ratio is defined as the amortized unpaid loan balance divided by the house value, estimated as the original house value adjusted by CoreLogic®'s county-level house price index.
Delinquent	Whether the borrower is delinquent in a given month.
Months Delinquent	The number of months within an episode of mortgage delinquency.
Ever Delinquent	Whether the borrower has ever been delinquent.
Delinquency Episodes	The number of mortgage delinquency episodes in the loan history.

[11] A financed upfront mortgage insurance premium could arguably be backed out of the unpaid balance of the mortgage and factored into the *PAV* instead of the *MAV*.

Monthly county-level economic conditions include—

Unemployment Rate	The unemployment rate reported by the Bureau of Labor Statistics.
Change in Employment	The 12-month change in the number of employed persons reported by the Bureau of Labor Statistics.
Mortgage Delinquency Rate	The serious mortgage delinquency rate, defined as the share of loans 90 days delinquent or in foreclosure reported by CoreLogic®.
Change in House Values	The 12-month change in the CoreLogic® house price index.
House Price Ratio	The estimated house value, computed by adjusting the value at origination by the CoreLogic® house price index, divided by the median sales price.
Homes Sales	The 12-month moving total number of property sales reported by CoreLogic®.

The author anticipated that the likelihood of assumption would increase with the contemporaneous LTV ratio (i.e., the share of the sales price that can be financed by the existing loan) and decrease with the strength of the local economy, when new mortgage credit might be more readily available.

In addition to the likelihood of assumption, the author further analyzed the *effect of assumption* on the likelihood of claim-default. Claim-default is defined as a mortgage insurance claim dated to the beginning of the delinquency episode that led to the claim (i.e., 1 month after the last payment made among loans that terminated with a mortgage insurance claim). This definition is preferred to the more often-used first 90-day delinquency because delinquent loans can be assumed; therefore, delinquency is not a competing risk to assumption. Only a terminated loan cannot be assumed. However, the date at which a claim is recorded depends on foreclosure, conveyance, and claims processes beyond the control of the borrower. Therefore, claim terminations in this paper are dated to the beginning of the default. Assumption becomes a time-varying binary indicator (*ASSUME*) in the loan history. If assumptions are used to bypass underwriting standards, as found by Allen and Springer (1998), then assumption may be associated with a greater credit risk. Assumption value and delinquency covariates are excluded, but the specification is otherwise similar. The focus is on the cause-specific effect of assumption, but both Cox and Fine-Gray models are estimated.

Findings

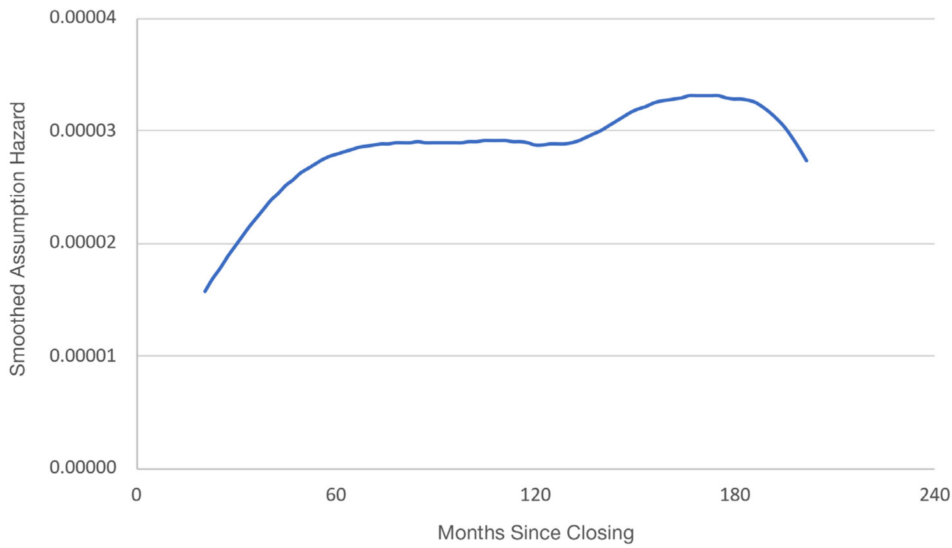
First are the findings related to the likelihood of assumption, then the results of the estimated effect of assumption on loan performance.

Assumption

Exhibit 10A shows the smoothed assumption hazard function estimated from the sample. The likelihood of assumption is relatively constant throughout the life of the loan. Exhibit 11 presents the results of assumption hazard models. The first three columns show the result of the cause-specific Cox hazard model, and columns four through six show the result of the Fine-Gray subdistribution model.

Exhibit 10A

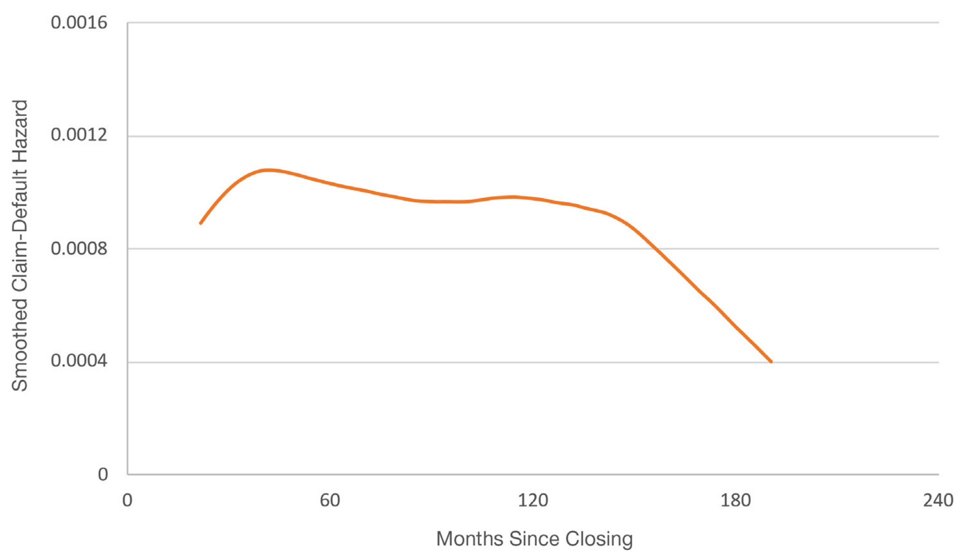
Baseline Hazards—Assumption



Source: Author's analysis of Federal Housing Administration administrative data

Exhibit 10B

Baseline Hazards—Claim-Default



Source: Author's analysis of Federal Housing Administration administrative data

Exhibit 11

Assumption Hazard

	Cox			Fine-Gray		
	(1)	(2)	(3)	(4)	(5)	(6)
Assumption Value ($000s)			1.017*** (0.002)			1.018*** (0.002)
Mortgage Assumption Value	1.019*** (0.003)	1.018*** (0.003)		1.017*** (0.002)	1.016*** (0.002)	
Premium Assumption Value		1.015*** (0.003)			1.021*** (0.004)	
Loan-to-Value Ratio	0.999 (0.005)	0.997 (0.005)	0.996 (0.004)	0.951*** (0.005)	0.948*** (0.004)	0.949*** (0.004)
Delinquency						
Currently Delinquent	0.991 (0.118)	0.995 (0.119)	0.997 (0.119)	0.738** (0.077)	0.753** (0.079)	0.748** (0.079)
Months Delinquent	1.041*** (0.003)	1.040*** (0.003)	1.039*** (0.003)	1.056*** (0.004)	1.054*** (0.004)	1.055*** (0.003)
Ever Delinquent	0.785*** (0.056)	0.784*** (0.056)	0.783*** (0.056)	0.816** (0.055)	0.817** (0.056)	0.818** (0.056)
Delinquency Episodes	0.990 (0.012)	0.990 (0.012)	0.991 (0.012)	1.075*** (0.012)	1.073*** (0.012)	1.073*** (0.012)
Economic Conditions						
Unemployment Rate	0.948* (0.022)	0.954* (0.022)	0.955* (0.022)	0.920* (0.034)	0.931* (0.032)	0.930* (0.033)
Change in Employment	1.023 (0.013)	1.022 (0.014)	1.021 (0.014)	1.014 (0.015)	1.013 (0.015)	1.014 (0.015)
Delinquency Rate	0.990 (0.010)	0.989 (0.010)	0.988 (0.010)	1.022 (0.015)	1.018 (0.013)	1.019 (0.013)
Change in House Values	0.972*** (0.005)	0.968*** (0.005)	0.967*** (0.005)	0.949*** (0.005)	0.945*** (0.005)	0.946*** (0.005)
Value Ratio	1.000*** (0.000)	1.000** (0.000)	1.000** (0.000)	1.000* (0.000)	1.000 (0.000)	1.000 (0.000)
Home Sales (Log)	0.934* (0.027)	0.929* (0.028)	0.928* (0.028)	0.875*** (0.027)	0.869*** (0.027)	0.870*** (0.027)
AIC	137,390	137,346	137,348	612	613	611

AIC = Akaike Information Criterion.

Notes: Cox model treats all other terminations as censored observations. Fine-Gray model treats other terminations as a competing hazard. Assumption Value includes both mortgage assumption value and premium assumption value.

*Statistically significant at the *** 0.001, ** 0.010, and * 0.050 levels. Errors clustered by state.*

23,407 subjects (1,203,119 observations). Standard errors in parentheses.

Source: Author's analysis of Federal Housing Administration administrative data

As expected, mortgage assumption is less common in strong housing markets. House price appreciation and homes sales are associated with statistically significant declines in the likelihood of assumption. In addition, the year fixed effects (not shown) are smallest before 2005, during the housing boom, and greatest in 2012 at the nadir of the housing market. On the other hand, higher unemployment is also associated with a lower likelihood of assumption.

Borrowers that have never been delinquent are more likely to have their loan assumed. However, the likelihood of assumption increases if the borrower is currently delinquent and increases with the number of months delinquent. Contrary to expectation, higher contemporaneous LTV ratios are associated with a lower likelihood of assumption in the Fine-Gray model, but are not statistically significant in the Cox model.

Finally, the top rows in exhibit 11 show the effect associated with the estimated assumption value. The first column includes just the MAV associated with the interest rate spread and remaining balance of the mortgage. Every $1,000 increase in MAV is associated with a 1.9 percent increase in the assumption hazard. The second column of exhibit 11 includes both the MAV and the value associated with the insurance premium schedule of the existing loan relative to the prevailing premium schedule. Every $1,000 increase in the PAV is associated with a 1.5 percent increase in the assumption hazard. Including PAV also slightly reduces the effect associated with MAV to 1.8 percent. However, the difference between the PAV and MAV coefficients is not statistically significant (χ^2=1.51). The third column sums mortgage and premium assumption values and finds every $1,000 increase in total assumption value is associated with a 1.7 percent increase in the assumption hazard. The Fine-Gray model produces comparable estimates of the impact of assumption value on the likelihood of assumption, although the effect associated with PAV is noticeably greater.

Claim-Default

Exhibit 10B shows the smoothed claim-default hazard function estimated from the sample. The likelihood of claim-default peaks within the first 5 years and then slowly declines. The first panel of exhibit 12 presents the results of claim-default hazard models. The first column shows the Cox model and the second column shows the Fine-Gray model.

Exhibit 12

Effect of Assumption

	A. Claim		B. FHA Refinance		C. Other Non-Claim	
	(1) Cox	(2) Fine-Gray	(3) Cox	(4) Fine-Gray	(5) Cox	(6) Fine-Gray
Assumed	0.591*** (0.068)	0.788* (0.093)	0.850* (0.066)	1.086 (0.087)	1.085* (0.036)	1.198*** (0.039)
Loan-to-Value Ratio	1.024*** (0.004)	1.014** (0.005)	1.027*** (0.004)	1.008* (0.004)	0.987*** (0.003)	0.951*** (0.002)
Economic Conditions						
Unemployment Rate	0.978 (0.014)	0.983 (0.016)	0.944*** (0.014)	0.921*** (0.021)	0.930* (0.027)	0.913** (0.026)
Change in Employment	0.976*** (0.006)	0.998 (0.008)	0.995 (0.009)	1.010 (0.010)	1.010 (0.016)	1.006 (0.017)
Delinquency Rate	1.056*** (0.011)	1.111*** (0.026)	0.963** (0.013)	0.987 (0.023)	0.900* (0.038)	0.925* (0.036)
Change in House Values	0.986*** (0.003)	0.989* (0.005)	1.012* (0.006)	1.005 (0.006)	1.029*** (0.003)	1.010*** (0.003)
Value Ratio	1.000 (0.001)	0.998 (0.001)	1.000*** (0.000)	1.000** (0.000)	1.000*** (0.000)	1.000** (0.000)
Home Sales (Log)	0.923*** (0.018)	0.863*** (0.022)	1.094** (0.034)	1.055 (0.037)	1.072*** (0.020)	1.035* (0.016)
AIC	6,402,260	86,114	22,080,705	86,114	45,390,610	173,408

AIC = Akaike Information Criterion.
Notes: Cox model treats all other terminations as censored observations. Fine-Gray model treats other terminations as competing hazard.
*Statistically significant at the *** 0.001 ** 0.010 * 0.050 level. Errors clustered by state.*
23,407 subjects (1,365,044 observations). Standard errors in parentheses.
Source: Author's analysis of Federal Housing Administration administrative data

As expected, the likelihood of claim-default declines with strong economic conditions. The likelihood is directly correlated with the mortgage delinquency rate but inversely correlated with home sales, house price appreciation, and job growth. Consistent with economic theory, the likelihood of claim default also increases with the contemporaneous LTV ratio.

Assumption is associated with a substantial and statistically significant decline in the likelihood of claim-default. The claim-default hazard declines more than 40 percent in the Cox proportional hazard model, which is most appropriate for causal inference. The estimate is smaller (a 21-percent decline) in the Fine-Gray model, which reflects the cumulative incidence.

The smaller effect of assumption found in the Fine-Gray model may be due to assumption being associated with an increase in non-claim terminations. Assumed loans may be less likely to go to claim simply because they are more likely to refinance or prepay. Although it is not the focus of this paper, the author estimated the effect of assumption on the likelihood of refinancing through FHA (panel B of exhibit 12) or otherwise terminating without claim (panel C), which includes selling the home, refinancing out of FHA, or prepaying some other way. Assumption is associated with a reduction in the likelihood of refinancing with FHA in the Cox model but is not significant in the Fine-Gray model. On the other hand, assumption is associated with an increase in the likelihood of other non-claim termination in both models.

Conclusion

Mortgage assumptions have been an obscure part of the mortgage market, mostly limited to government-insured loans. Even the actuarial review of FHA's Mutual Mortgage Insurance Fund, which requires many economic assumptions, does not mention mortgage assumptions (Pinnacle, 2021). However, the number of mortgage assumptions may increase in the near future for three reasons. First, the market has more mortgages eligible to be assumed. At the end of 2020, the number totaled nearly 8 million active FHA-insured loans, accounting for roughly 10 percent of all owner-occupied households and 16 percent of homes with a mortgage, more than twice the comparable figures in 2005. Second, mortgage rates have already jumped from historic lows. The average interest rate on new 30-year fixed-rate mortgages reached over 5 percent by May 2022 and may continue to increase. By contrast, the median contract rate on active FHA-insured loans was only 3.875 percent. When these borrowers decide to sell their properties, they may also be able to sell their below-market rate mortgages. Finally, Congress has debated legislation that would reinstitute the premium cancellation.[12] Premium cancellation influences the premium assumption value, which has as much if not more effect than the mortgage assumption value. Real estate and mortgage industry professionals may want to become more familiar with the mechanics and benefits of mortgage assumption as options for interested borrowers.

The findings of this paper show that both the mortgage assumption value, based on the remaining mortgage payments and spread between mortgage and market interest rates, and the premium assumption value, based on the difference between mortgage and current insurance premium schedules, influence the likelihood of assumption. Every additional $1,000 in assumption value increases the assumption hazard by nearly 2 percent. Higher likelihood of assumption is also correlated with weaker housing markets and borrowers in delinquency. Mortgage assumption is subsequently associated with a significant reduction in the likelihood of default. The combination of delinquency increasing the likelihood of assumption and assumption reducing the likelihood of claim suggests that assumability may help reduce risk to FHA. Nevertheless, FHA should develop methods to efficiently process assumption applications in a timely manner while ensuring adequate evaluation of the credit risk of assumptors given that they are not processed through regular automated underwriting. Furthermore, the probability and impact of assumptions should be appropriately accounted for in actuarial reviews. Assumable loans cannot be presumed to prepay and otherwise behave as other loans that exercise due-on-sale clauses.

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[12] Making FHA More Affordable Act of 2017, HR 4159, 115th Congress (2017).

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Real and Personal: The Effect of Land in Manufactured Housing Loan Default Risk

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The views expressed in this article are those of the author and do not represent the official positions or policies of the Office of Policy Development and Research, the U.S. Department of Housing and Urban Development, or the U.S. government.

Abstract

Ownership of manufactured housing is complicated by the distinction between homeownership and landownership. Roughly two of five manufactured homeowners do not own the underlying land. Traditional mortgage financing is only available for manufactured homes owned with land as real estate. Personal loans are available for manufactured homes without land or owned as personal property but are often more expensive.

The Federal Housing Administration (FHA) provides loan insurance for the purchase or refinance of manufactured homes owned as either real or personal property. This paper provides an overview of the Title I loan insurance program and compares the default risk of FHA-insured personal property loans for the purchase of manufactured homes to similar mortgages for manufactured homes. Landownership, even when the home is titled as personal property, makes an important difference in risk.

Introduction

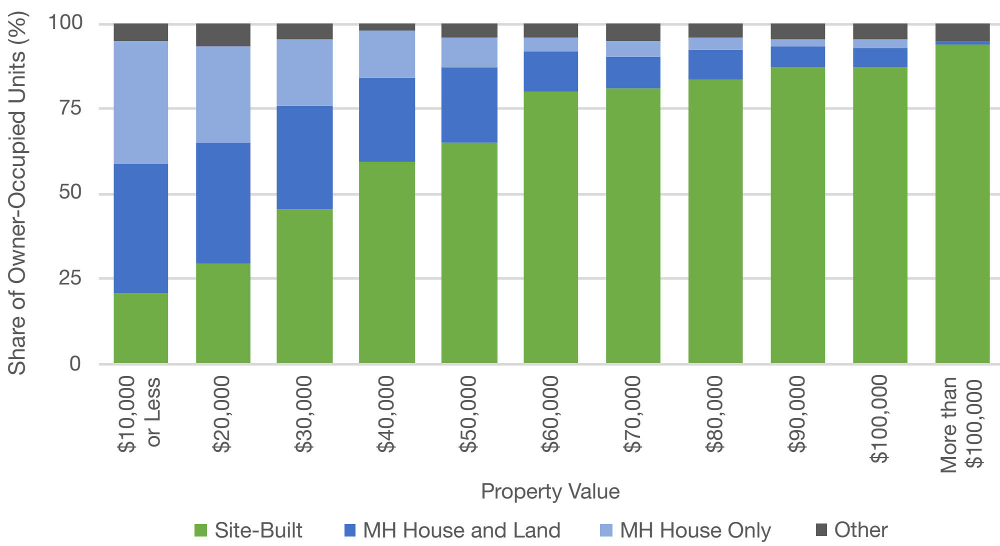
Manufactured homes provide an important source of affordable housing in the United States. The price per square foot of a typical new manufactured home is less than one-half that of a new, traditionally site-built home, excluding land value ($52.80 vs. $109.14).[1] Manufactured homes account for more than one-half of all owner-occupied housing units less than $50,000 (exhibit

[1] Median values for 2019 from the Census Bureau's Survey of Construction and author tabulations of the Manufactured Housing Survey.

1). According to the 2019 American Housing Survey, nearly 6.4 million households in the United States (roughly one in 20 households) live in manufactured homes. Most of those households own their home.

Exhibit 1

Owner-Occupied Property Type by Value, 2019

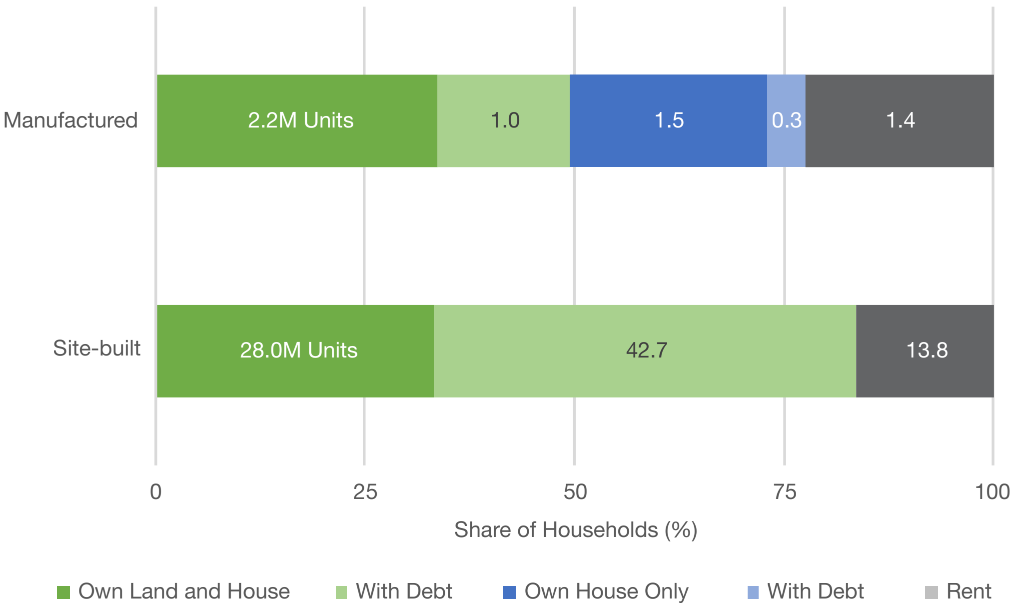


MH = Manufactured Housing.
Note: Value of manufactured homes includes only the value of the housing unit, even if owned with land.
Source: American Housing Survey

However, ownership of manufactured housing is more complicated than ownership of site-built homes. Nearly one-half of households in manufactured homes own both the housing unit and the underlying land (exhibit 2). Another 28 percent own the housing unit only and not the lot. Traditional mortgage financing is only available for real property, meaning the homeowner must own the land and the home must be fixed to a permanent foundation. Personal loans are available for households who do not own, or who choose not to encumber, the land but are often more expensive with shorter terms. According to the 2019 American Housing Survey, only 16 percent of manufactured-home owners without land report having a loan on the unit, whereas nearly one-third of manufactured-home-and-landowners and more than 60 percent of site-built single-family-home owners have loans on their properties.

Exhibit 2

Site-Built and Manufactured Housing Tenure and Mortgage Status, 2019



Source: American Housing Survey

For more than five decades, the Federal Housing Administration (FHA) has provided loan insurance to facilitate the purchase of manufactured homes not only as real property through its flagship Section 203(b) program but also as personal property under Title I of the National Housing Act; however, the latter program has declined in recent decades. This paper provides an overview of FHA's Title I manufactured housing loan program and analyzes the performance of these loans relative to FHA-insured mortgages for the purchase of manufactured homes held as real property. Land ownership, even when not used to secure a loan as collateral, substantially reduces the likelihood of default.

Manufactured Housing

Under the National Manufactured Housing Construction and Safety Standards Act of 1974 (Public Law 93-383), the U.S. Department of Housing and Urban Development (HUD) issues and enforces standards for the design, construction, and installation of manufactured housing, preempting state and local laws. Manufactured housing—as opposed to mobile homes, trailers, and modular homes—is defined as a prefabricated dwelling built on a permanent chassis after June 15, 1976, in compliance with this "HUD Code."

Manufactured homes can be owned as either real or personal property. Jointly holding land and a manufactured home affixed to a permanent foundation makes it nearly indistinguishable from site-built homes from a legal perspective. Personal or "chattel" property covers only the housing unit. Most owners of manufactured homes (64 percent) are also landowners. Only 19 percent of new manufactured home shipments, however, were titled as real property in 2019, according to the Manufactured Housing Survey; by contrast, 76 percent were titled as personal property.

Ownership and title affect financing options. Traditional mortgage financing is available only for real property. Russell et al. (2021) found that almost one-half of borrowers using personal property loans to purchase a manufactured home leased the land. Another 24 percent lived rent free on land owned by others, possibly family members. However, more than one-fourth (27 percent) owned the land but still used personal property loans rather than mortgage financing.

Russell et al. (2021) also found that applications for personal property loans to purchase manufactured homes are more likely to be denied than manufactured home mortgage applications, which are more likely to be denied than mortgage applications for a site-built home, even controlling for credit score. Similarly, the average annual percentage rate (APR) on personal property manufactured housing loans is 3.6 percentage points higher than the APR for manufactured home mortgages, which is 1.2 percentage points higher than the APR for site-built home mortgages.[2] Chattel financing also is not covered by the same consumer protection laws, including the Real Estate Settlement Procedures Act (CFPB, 2014).

The Center for Community Capital (CCC, 2020) surveyed borrowers who financed the purchase of a manufactured home in Texas in 2018. They found that 61 percent of buyers of manufactured homes owned the underlying land. First-time homebuyers and lower-income, African-American, and urban homebuyers were less likely to be landowners. Among landowners, 59 percent titled their home as personal property. Some landowners preferred to avoid encumbering the land, even if personal loans were associated with higher interest rates. Using a personal property loan was associated with more knowledge of the loan process and less reliance on lenders and real estate agents for information but a greater likelihood of applying through or being referred by the seller. Borrowers using personal loans disproportionately preferred shorter loan terms, whereas borrowers using mortgage loans preferred lower closing costs and fixed interest rates.

Whether ownership of manufactured homes includes landownership is immensely consequential for evaluating its effects on wealth. Jewell (2003) and Boehm and Schlottmann (2008) found that ownership of a manufactured home with landownership is associated with similar average but more volatile price appreciation compared with site-built homes. Similarly, the Federal Housing Finance Agency (FHFA, 2018) constructed a repeat-sales index of only manufactured housing transactions and found price trends similar to those for other forms of housing. Manufactured housing prices rose 120 percent between 1995 and 2018, compared with 140 percent for other forms of housing, although manufactured housing prices fell more during the Great Recession. However, the FHFA index is based on mortgage acquisitions by Fannie Mae and Freddie Mac (i.e., manufactured homes owned with land as real property). By contrast, Jewell (2003) and Boehm and Schlottmann (2008) found that ownership of manufactured homes without landownership is associated with depreciation relative to house price changes among site-built homes. Manufactured housing "in which the household does not own the lot is not an investment in any sense. It should be thought of as a type of consumer durable" (Boehm and Schlottmann, 2008: 200).

[2] Russell et al. (2021) also found substantial bunching at APR spreads just below the thresholds under the Home Ownership and Equity Protection Act that would require additional disclosure requirements.

The effect of title and landownership is further complicated by the correlation with construction status. The Home Mortgage Disclosure Act does not identify new construction but, since 2018, has identified whether a manufactured housing loan is for the house and land or the house alone. Nearly 225,000 loans for the purchase of manufactured homes were reported in 2018 and 2019, of which the majority (55 percent) are for the housing unit and land. According to the Manufactured Housing Survey, this number of purchase loans for manufactured homes and land is several times the number of new manufactured home sales titled as real property, suggesting that most of those loans are for existing manufactured homes. For comparison, the number of purchase loans for manufactured homes without land is close to the number of new manufactured home sales titled as personal property, suggesting that most of those loans are for new housing units. A premium for new consumer durables has long been discussed in economic theory, particularly for automobiles (e.g., Akerlof, 1970; Bond, 1982; Cramer, 1958), and has been empirically extended to new homes (Coulson, Morris, and Neill, 2019). Any price premium for new durables is lost as soon as they are bought, appearing as excessive depreciation. Therefore, some of the depreciation associated with a lack of landownership may be the loss of the premium for new manufactured homes.

The difference in appreciation affects loan performance, given the importance of equity as a key determinant of default, which is well established in the economic literature on mortgages (e.g., LaCour-Little, 2008; Quercia and Stegman, 1992). There has been a paucity of research specifically on the loan performance of manufactured homes (Lawrence, Smith, and Rhoades, 1992). Myers and Forgy (1963) demonstrated the value of developing credit risk scoring systems using discriminant analysis of a sample of conditional sales contracts on mobile homes. Notable factors include whether the borrower has a bank account, unsatisfactory credit references, history of repossessions and bankruptcies, the unpaid balance and downpayment, other terms of the sales contract, the width of the mobile home, and whether it was new or used. Lawrence, Smith, and Rhoades (1992) used logistic regression to estimate the likelihood that a sample of loans active in 1988 would default the following year. Borrowers' current equity is estimated by assuming a depreciation rate of 10 percent in the first year and 5 percent in subsequent years. Lower equity, higher initial payment-to-income ratios, a history of missed payments, smaller loans, older borrowers, and higher statewide unemployment rates are associated with greater risk.

Loans for manufactured homes experienced a wave of reckless lending and subsequent defaults in the 1990s that presaged the subprime mortgage crisis. More than 75,000 owners had their homes repossessed in 2000. Manufactured housing lender Conseco, Inc., which accounted for most loan originations that year, filed for bankruptcy in 2002 (CFPB, 2014).[3] Genz (2001) noted that loans for manufactured homes default at a rate four times higher than conventional loans, which would be "unthinkable in the world of 'real housing' finance, but somehow tacitly accepted for people who make their home in a factory-built unit" (Genz, 2001: 403). However, there has not been an explicit and rigorous comparison of loan performance for manufactured housing as real and personal property.

[3] Conseco was also a major Title I lender in the early 1990s (see exhibit 3).

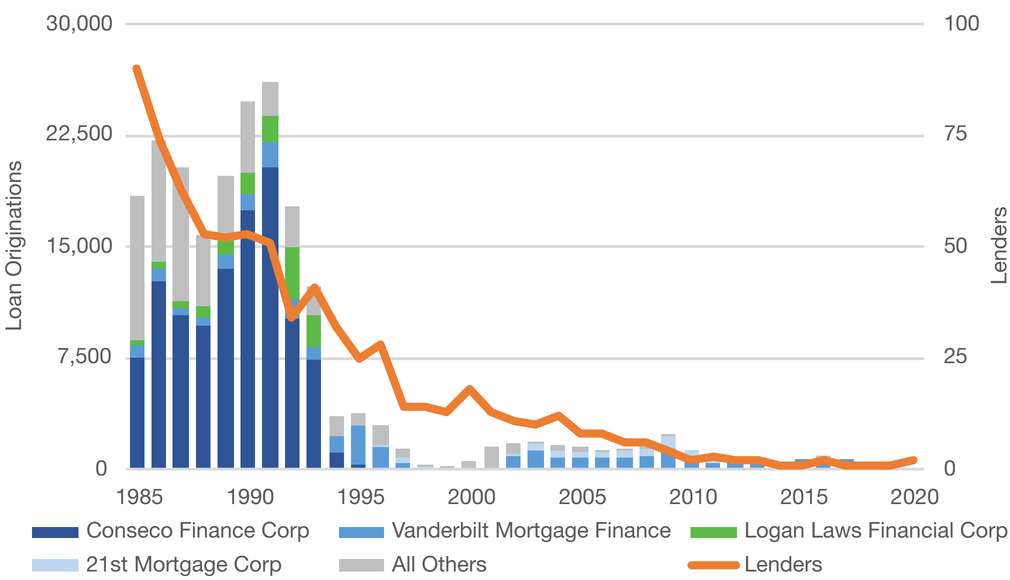
Title I

HUD plays an important role in manufactured housing in the United States. In addition to regulating the construction and safety standards of manufactured homes, HUD helps finance the purchase and refinance of manufactured homes through FHA. FHA has always insured loans on manufactured and mobile homes as real property if they meet its Minimum Property Standards and local building and land use regulations. However, the Housing and Urban Development Act of 1969 (Public Law 91-152) also authorizes FHA to insure personal property loans secured by manufactured housing. Borrowers are not required to own the land but must have a land lease that does not expire for at least 3 years after origination and afterward is renewable on an annual basis. Insurance is authorized under Title I of the National Housing Act rather than Section 203(b) and financed through the General Insurance Fund rather than the Mutual Mortgage Insurance Fund.

CCC (2020) reported that FHA accounted for 14 percent of buyers of manufactured homes in Texas in 2018 using chattel financing, compared with 22 percent using mortgages. However, Title I volume is a fraction of what it was three decades ago. FHA-insured chattel loan originations collapsed from more than 26,000 in 1991 to fewer than 225 in 1999 (exhibit 3). Originations rebounded to nearly 2,000 a year in the early 2000s. Nevertheless, FHA has insured nearly 30 times more loans for purchase or refinance of manufactured housing titled as real estate through its main 203(b) mortgage insurance program than titled as personal property through Title I since 1998. Two major reasons for the decline are a limited secondary market and low loan limits.

Exhibit 3

Title I Lenders and Loan Volume, 1985–2020

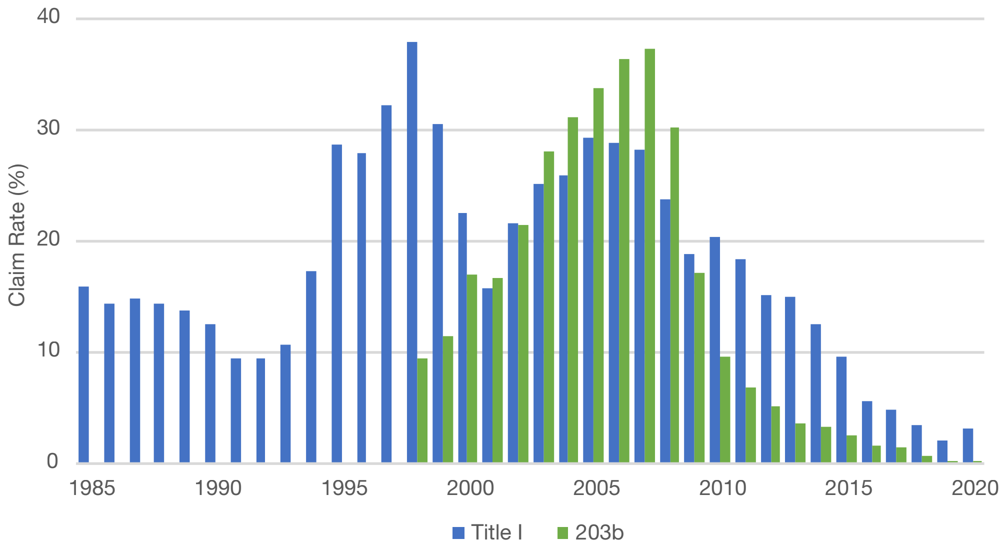


Source: Federal Housing Administration administrative data

Ginnie Mae has facilitated securitization of Title I loans since the 1970s but significantly curtailed operations after suffering losses. Title I insurance covers only 90 percent of the claim amount, compared with full coverage under 203(b). In addition, FHA's liability had been capped at 10 percent of a lender's aggregate disbursement, known as the reserve account. Those limits became binding when manufactured housing suffered waves of defaults in the 1980s and 1990s. Nearly 29 percent of Title I loans originated between 1995 and 2000 terminated with a claim (exhibit 4). Although co-insurance was meant to align incentives between FHA and lenders, it created a moral hazard problem: "[A]s lenders' portfolios experienced losses [beyond the 10-percent aggregate disbursement cap], they were incented to make more loans in order to increase the amount of claims payments for which they were eligible" (Frenz, 2006: n.d.).

Exhibit 4

FHA Manufactured Housing Claim Rate by Cohort, 1998–2020



Source: Federal Housing Administration administrative data

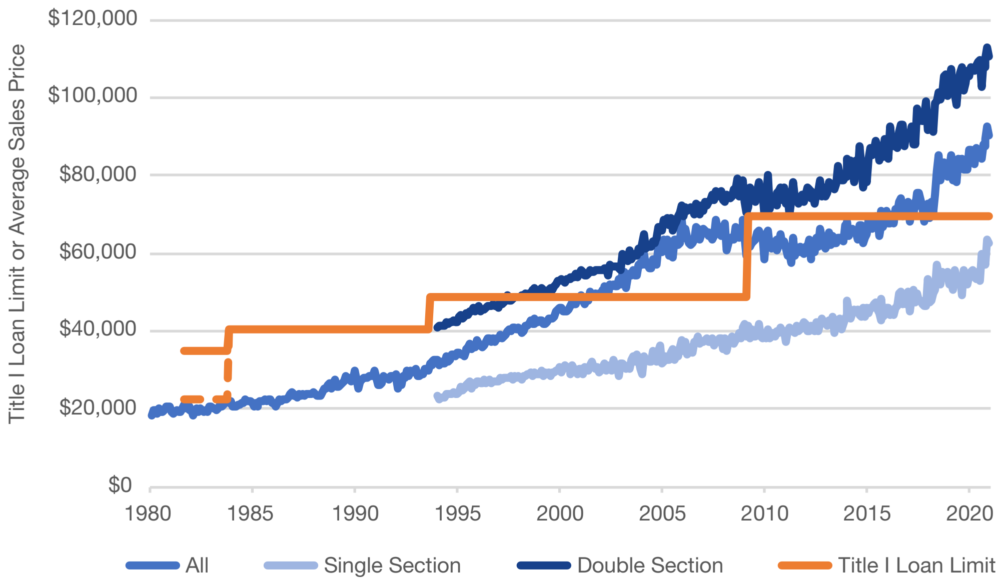
Those losses were pushed onto Ginnie Mae, which guarantees an issuer will make payments on securities backed by Title I loans. Ginnie Mae placed a moratorium on new manufactured housing securities issuers after 12 issuers defaulted between 1986 and 1988. Another 10 issuers defaulted in the 1990s, resulting in at least $514 million in losses for Ginnie Mae (Government Accountability Office, 2007). The FHA Manufactured Housing Loan Modernization Act of 2008 removed the portfolio cap to provide loan-level insurance coverage similar to the 203(b) program. Nevertheless, Ginnie Mae requires issuers to have a minimum net worth of $10 million plus 10 percent of outstanding obligations to participate in its Manufactured Home Program, compared with only $2.5 million plus 0.2 percent of outstanding obligations for the Single-Family Program.

The second major reason for declining Title I origination volume is that loan limits failed to keep pace with the rising costs of manufactured homes (exhibit 5). Before 1983, there were separate loan limits for one- and two-section manufactured homes. Congress then raised the limit to

$40,500 but removed the distinction by number of sections. The Housing and Community Development Act of 1992 again increased the loan limit for a manufactured home to $48,600, above the average sales price of two-section homes at the time. However, by 2001 the average sales price of all new units exceeded the loan limit. The FHA Manufactured Housing Loan Modernization Act increased the limit to $69,678, roughly the average price of a new unit. The 2008 Act also mandated annual indexing of loan limits. However, the average sales price of new units fell in the years shortly following the Great Recession. Rather than lower the loan limit in proportion to the decline in price, FHA kept them unchanged. By 2016, the average sales price had again risen above the Title I loan limit, but limits were not increased to keep pace.

Exhibit 5

Title I Loan Limit and Manufactured Housing Sales Prices, 1980–2020



Note: Manufactured housing unit only.

Sources: Public Law 98-181; FHA Title I Letters 424, 480; Manufactured Housing Survey

Title I requires an upfront mortgage insurance premium of 2.25 percent, higher than the 1.75 percent in the 203(b) program, and an annual insurance premium of 1 percent, also generally higher than the 203(b) program. The maximum loan term for a loan on a manufactured home is 20 years and 32 days, less than the 30 years common in the 203(b) program. The housing payment, which includes taxes and lot rent, cannot exceed 33 percent of effective borrower income, and total debt payments cannot exceed 45 percent.

There is no minimum credit score, but the lender must pull a score if available and examine the borrower's overall pattern of credit behavior. In addition, the maximum loan-to-value (LTV) ratio is lower (90 percent) if the borrower has a credit score lower than 500. Otherwise, the maximum LTV ratio is 95 percent, less than the 96.5-percent maximum in the 203(b) program. However, the comparison is not apples to apples. The Title I denominator "value" is the sum of 130 percent of the wholesale price plus eligible itemized options, sales tax, transportation cost, cost of installing appurtenance and air conditioning or heat pump, and financeable fees and charges. The upfront mortgage insurance premium can be financed but counts toward the loan limit, whereas it does not count in the 203(b) program. Secondary financing is not permitted in Title I.

The Title I program has gradually suffocated from the lack of a secondary market, failure to increase loan limits with the rising cost of manufactured homes, and antiquated paper-based program procedures. Fewer than 35 loans were originated under the program in 2020, and roughly 8,000 loans were still active at the end of 2021.

Data

This study used administrative data from FHA's 203(b) and Title I loan insurance programs to analyze the performance of personal property loans relative to comparable mortgages for the purchase of manufactured homes originated between 2012 and 2018. Roughly 2.5 percent of observations were dropped due to incomplete information, mostly credit score. The resulting sampling frame consists of nearly 127,000 observations, of which roughly 3,900 (3 percent) are Title I loans. Exhibit 6 provides descriptive statistics of the data.

Exhibit 6

Descriptive Statistics (1 of 2)

	Title I	203(b)	
		Matched	All
Observations	3,944	9,190	122,831
Weighted	3,944	3,944	
Estimated Title I Probability (%)	18.4	15.4	2.6
Loan Status (%)			
Active	83.9	77.8	74.6
Default-Claim	7.8	4.6	2.1
Prepaid	8.3	17.7	23.3
Sales Price ($2021)	57,910	144,756	151,129
	(14,139)	(44,291)	(96,124)
New Construction (%)	91.9	91.9	12.6
Loan Amount ($2021)	55,725	133,647	144,938
	(13,698)	(41,291)	(69,797)
LTV Ratio (%)	96.8	92.7	96.5
	(9.2)	(7.7)	(5.2)
Loan Term (Months)	239	359	357
	(6)	(11)	(21)
Interest Rate (%)	7.3	4.5	4.5
	(0.5)	(0.5)	(0.6)
Rate Spread	3.3	0.5	0.3
	(0.5)	(0.5)	(0.5)
Credit Score	660	654	683
	(55)	(42)	(48)
Income ($2021)	3,547	4,255	4,915
	(1,568)	(1,823)	(2,442)

Exhibit 6

Descriptive Statistics (2 of 2)

	Title I	203(b)	
		Matched	All
Housing Ratio (%)	21.7	25.4	24.0
	(8.6)	(8.0)	(8.8)
Debt Ratio (%)	38.3	40.5	39.0
	(14.1)	(8.7)	(9.4)
Coborrower (%)	25.2	31.7	34.0
Age	42.9	43.5	39.9
	(17.3)	(14.0)	(13.8)
First-Time Buyer (%)	60.3	51.6	79.3
Race			
White	72.5	67.1	76.9
African-American	9.7	13.3	3.3
Hispanic	4.3	3.4	11.2
Other	2.4	2.8	1.6
Not Available	11.0	13.4	6.9
Rural-Urban (%)			
Urban Center	32.5	26.4	33.5
Urban Commuting	28.8	29.3	31.1
Micropolitan Area	19.7	21.5	19.6
Small Town	12.0	14.5	9.1
Rural	7.1	8.2	6.7
Year (%)			
2012	14.4	14.4	9.7
2013	11.7	11.7	9.7
2014	10.4	10.4	11.1
2015	16.0	16.0	14.9
2016	20.6	20.6	16.5
2017	16.8	16.8	18.2
2018	10.1	10.1	19.9
State (%)			
Other	12.9	12.9	65.6
Alabama	9.2	9.2	1.2
Arkansas	4.4	4.4	0.8
Kentucky	7.2	7.2	2.6
Louisiana	9.9	9.9	2.6
Mississippi	3.7	3.7	0.4
North Carolina	9.7	9.7	6.7
Oklahoma	3.3	3.3	1.6
South Carolina	6.0	6.0	2.6
Tennessee	7.1	7.1	3.6
Texas	17.8	17.8	8.5
Virginia	4.6	4.6	2.7
West Virginia	4.2	4.2	0.9

LTV = loan-to-value.

Note: Standard deviations shown in parentheses.

Source: Federal Housing Administration administrative data

Selection

Before comparing loan performance, this study analyzed differences between manufactured home mortgages and personal property loans. The results of this analysis were used to reduce differences that might confound estimating the relative risk of Title I loans.

Methodology

This study used a binomial logistic regression to estimate the likelihood of using Title I as opposed to 203(b) insurance.[4]

$$\log\left(\frac{P(TitleI)}{P(203b)}\right) = \beta X + \gamma Z + \theta + \varphi$$

Borrower level covariates *X* used to predict program and property type include:

Credit Score	The decision credit score of the borrower (i.e., the median of the scores from the three credit bureaus, or minimum if fewer than three are available). If multiple borrowers are present, then the lowest decision score is used.
Income	The natural logarithm of the inflation-adjusted monthly income (with Winsorization[5] to limit the influence of outliers) used in underwriting.
Co-Borrower	A binary indicator of whether more than one borrower is on the loan.
Age	The age of the primary borrower.
Race	Categorical variables reflecting the race and ethnicity of the primary borrower.
First-Time Buyer	A binary indicator of whether the borrowers are first-time homebuyers.

Housing market conditions Z at the time of closing include the following:

Unemployment	The monthly county unemployment rate reported by the U.S. Bureau of Labor Statistics.
MH Share	The number of manufactured housing units as a share of the total housing stock estimated in the most recent 5-year American Community Survey before loan origination.
RUCA	The rural-urban commuting area (RUCA) 2010 classification of the property ZIP Code developed by the U.S. Department of Agriculture. The classification is condensed into five categories: Urban Center (RUCA code 1), Urban Commuting Area (2–3), Micropolitan Area (4–6), Small Town (7–9), and Rural (10).

[4] Logistic regression estimated using the *logit* command in Stata/SE 15.0.

[5] Winsorization refers to top- and bottom-coding values at given percentiles. In this case, the top and bottom one percent of income values are replaced with 99^{th} and 1^{st} percentiles, respectively.

Fixed effects are included for the year the loan was closed θ and the 12 states with the most Title I manufactured housing loans φ. All other states are grouped in the reference category.

Findings

The first column of exhibit 7 presents the results of the logistic regression estimating the likelihood of using a Title I personal property loan for the purchase of a manufactured home relative to a 203(b) mortgage. Borrowers with lower income and lower credit scores were more likely to use Title I. Older homebuyers were also more likely to use Title I, whereas Hispanic and first-time buyers were less likely. Buyers in the most urbanized areas were more likely to use Title I, and 203(b) mortgages were more common within micropolitan areas and commuting zones of metropolitan areas.

Exhibit 7

Selection Model (1 of 2)

	(1)	(2)	(3)
New Construction		66.390***	76.810***
		(4.5420)	(7.3890)
Credit Score	0.988***	0.993***	0.993***
	(0.0005)	(0.0005)	(0.0007)
Income (Log)	0.145***	0.082***	0.089***
	(0.0073)	(0.0049)	(0.0074)
Co-Borrower	1.017	0.749***	0.791***
	(0.0458)	(0.0361)	(0.0527)
Age	1.012***	1.007***	1.008***
	(0.0013)	(0.0015)	(0.0021)
Race			
African-American	1.395***	0.750***	0.699**
	(0.0900)	(0.0557)	(0.0766)
Hispanic	0.560***	0.608***	0.612***
	(0.0470)	(0.0557)	(0.0720)
Other	2.022***	1.539**	1.021
	(0.2440)	(0.2260)	(0.2490)
Not Available	1.810***	1.324***	1.649***
	(0.1060)	(0.0893)	(0.1430)
First-Time Buyer	0.342***	0.511***	0.461***
	(0.0130)	(0.0236)	(0.0294)
Housing Market			
Unemployment Rate	1.071***	1.087***	1.019
	(0.0104)	(0.0130)	(0.0213)

Exhibit 7

Selection Model (2 of 2)

	(1)	(2)	(3)
MH Share of Stock	1.019***	1.006*	0.999
	(0.0024)	(0.0027)	(0.0054)
Land Value (Log)			76.810***
			(7.3890)
Land Share of Value			1.610***
			(0.2320)
Home Sales Rate			0.019***
			(0.0174)
Change in House Prices			0.985***
			(0.0022)
Mortgage Delinquency Rate			0.989
			(0.0097)
RUCA			
Urban Commuting	0.592***	0.549***	0.548***
	(0.0285)	(0.0305)	(0.0375)
Micropolitan Area	0.824***	0.692***	0.651***
	(0.0444)	(0.0431)	(0.0594)
Small Town	0.918	0.714***	0.650*
	(0.0602)	(0.0562)	(0.1140)
Rural	0.992	0.708***	0.586*
	(0.0781)	(0.0659)	(0.1250)
Observations	126,775	126,775	82,399
χ^2	6793***	8103***	4543***
AIC	25,423	17,260	9,136

AIC = Akaike information criterion. MH = manufactured housing. RUCA = rural-urban commuting area codes.

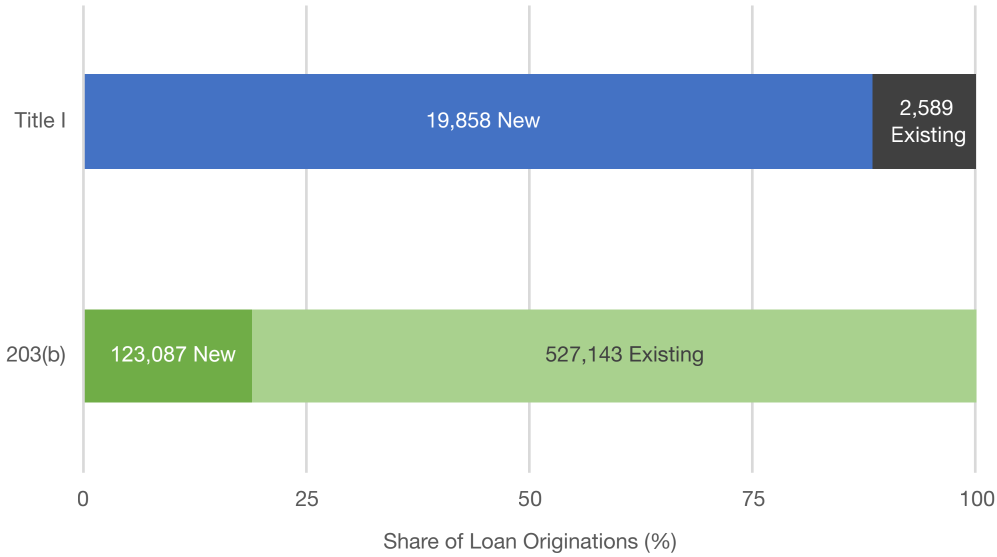
*Notes: State and year fixed effects not shown. Statistically significant at the * 0.050 ** 0.010 *** 0.001 level. Robust standard errors shown in parentheses.*

Source: Federal Housing Administration administrative data

The second column in exhibit 7 includes a binary indicator of construction status. Most (88 percent) Title I loans were for the purchase of new manufactured homes, whereas most (81 percent) 203(b) mortgages for manufactured homes were for the purchase of existing homes (exhibit 8). Even controlling for other characteristics, purchasing a new rather than existing manufactured home increased the odds of using Title I by a factor of 66.

Exhibit 8

FHA Manufactured Housing Lending by Construction Status, 1998–2020



Source: Federal Housing Administration administrative data

The unemployment rate and manufactured share of the housing stock were correlated with increased use of Title I. However, the third column of exhibit 7 adds additional housing market conditions, which causes both of those variables to lose statistical significance. The additional factors were not available for more than one-third of observations, reflecting the general lack of data in many rural areas. For those observations with complete information, higher land values were associated with increased use of Title I, whereas hot housing markets (home sales and house price appreciation) were associated with more 203(b) mortgages.

Propensity Score Matching

This study used propensity score matching to control for observable differences in homebuyers titling their manufactured homes as personal and real property. The propensity score is the log odds of using a Title I derived from the first logistic regression specification shown in exhibit 7.

This paper stratified the matching process by year, state, and construction status. The analysis matched each Title I loan for a new manufactured home to five 203(b) mortgages for new manufactured homes in the same state and year using nearest-neighbor matching with replacement.[6] In addition, the study matched Title I loans for existing manufactured homes to 10 203(b) mortgages for existing manufactured homes.

Matching reduced the sample size to 13,134 loans but substantially improved the overlap in borrower characteristics. Exhibit 6 shows how matching and weighting observations reduced differences in borrower characteristics and location, which allowed any differences in default risk

[6] Propensity score matching executed using the *psmatch2* command in Stata from Leuven and Sianesi (2003).

to be more specifically associated with the type of loan. However, differences remain that may affect relative loan performance. For example, Title I borrowers continued to be lower income than 203(b) borrowers. Matching did not meaningfully change the higher interest rate associated with Title I loans: the raw difference of 2.83 percentage points narrows slightly to 2.76 percentage points after matching but remains statistically significant.

Default

Default in this analysis is defined as an insurance claim dated to the start of the delinquency episode. This outcome definition addresses differences in the claim and property disposition processes between the two programs. Nearly 8 percent of Title I loans originating in the study period have terminated in a claim, compared with roughly 2 percent of 203(b) manufactured home mortgages. After propensity score matching, the claim rate of 203(b) mortgages increases to nearly 5 percent, still below the Title I default-claim rate.

Methodology

A Cox proportional hazard model estimates the additional default risk associated with Title I loans as

$$\lambda(t) = \lambda_0(t)e^{\delta T+\beta X+\gamma Z+\theta+\varphi}$$

where λ_0 indicates an unspecified baseline hazard.[7] Loan performance is censored at the end of 2019 to avoid problems arising from the COVID-19 pandemic.[8] Exhibit 9 shows the cumulative hazard of default by loan type before and after propensity score matching. The results show that the matching reduces the higher default hazard associated with Title I loans.

The coefficient of interest δ captures the difference in default risk associated with Title I loans relative to 203(b) mortgages. Borrower covariates X and housing market conditions Z are the same first specification of the selection model. The study analyzes the effects associated with the following additional risk factors:

Housing Ratio	Total housing payments, including the amount of lot rent for Title I borrowers, relative to borrower income. Often referred to as the “front-end” debt-to-income (DTI) ratio.
Debt Ratio	Total fixed payments, including housing and all other debt, relative to borrower income. Often referred to as the “back-end” DTI ratio.
New Construction	A binary indicator of whether the housing unit is new construction.
Rent Lot	A binary indicator of whether a Title I borrower pays lot rent.

[7] Cox hazard is estimated using the *stcox* command in Stata/SE 15.0.

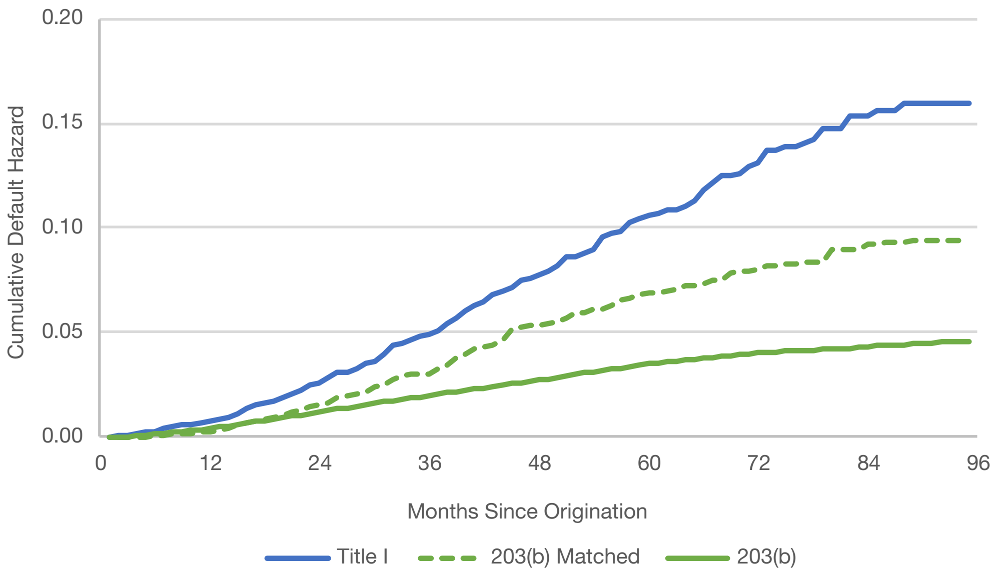
[8] Wong (2021) reports that owners of manufactured homes were more likely to be behind in their housing payments during the COVID-19 pandemic. Most personal property loans for manufactured homes were not covered by CARES Act relief provisions.

Land Tenure	A categorical variable indicating the type of land tenure, including (1) ownership, (2) leased private property, (3) leased park community, or (4) other.

Housing and debt ratios are also Winsorized to limit the influence of outliers.

Exhibit 9

Cumulative Default Hazard



Source: Federal Housing Administration administrative data

Findings

Exhibit 10 presents the results of the Cox proportional hazard model. The first specification shows that the baseline difference is default risk before propensity score matching and with no covariates. Title I loans are associated with a risk of claim-default nearly three times higher than 203(b) mortgages. That difference narrows after propensity score matching. The second column of exhibit 10 shows that Title I loans are associated with a 56-percent increase in the risk of default relative to 203(b) mortgages with similar borrower characteristics.

Exhibit 10

Default Hazard Ratios

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Title I	2.995***	1.557***	1.430***	1.671***	1.687***	1.465**	1.172
	(0.179)	(0.161)	(0.146)	(0.205)	(0.212)	(0.203)	(0.213)
Credit Score			0.995***	0.996***	0.996***	0.996***	0.996***
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Income (Log)			0.772*	1.199	1.232	1.090	1.187
			(0.085)	(0.213)	(0.227)	(0.204)	(0.224)
Co-Borrower			0.762*	0.680*	0.682*	0.689*	0.692*
			(0.101)	(0.113)	(0.113)	(0.114)	(0.114)
Age			1.016***	1.016***	1.016***	1.016***	1.017***
			(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Race							
African-American			0.683*	0.653**	0.654**	0.662**	0.666*
			(0.108)	(0.105)	(0.105)	(0.106)	(0.107)
Hispanic			0.482**	0.462**	0.462**	0.457**	0.472**
			(0.133)	(0.129)	(0.129)	(0.128)	(0.132)
Other			0.444*	0.422*	0.423*	0.438*	0.429*
			(0.166)	(0.158)	(0.158)	(0.163)	(0.160)
Not Available			0.785	0.782	0.784	0.780	0.786
			(0.189)	(0.192)	(0.192)	(0.191)	(0.193)
First-Time Buyer			1.536***	1.524***	1.521***	1.491***	1.456**
			(0.183)	(0.182)	(0.182)	(0.178)	(0.174)
Housing Ratio				1.024**	1.026**	1.020*	1.023*
				(0.009)	(0.009)	(0.009)	(0.009)
Debt Ratio				1.005	1.005	1.005	1.004
				(0.005)	(0.005)	(0.005)	(0.005)
New Construction					0.864	0.879	0.860
					(0.127)	(0.130)	(0.128)
Rent Lot						1.309*	
						(0.162)	
Land Tenure							
Leased Park Community							1.794**
							(0.336)
Leased Private Property							1.458*
							(0.237)
Other							1.586
							(0.916)
Observations	126,775	13,134	13,134	13,134	13,134	13,134	13,134
χ^2	338***	18***	190***	204***	204***	212***	228***
AIC	64,812	8,173	8,120	8,113	8,114	8,112	8,110

AIC = Akaike information criterion.

Note: Unemployment rate, manufactured share of housing stock, and state and year fixed effects not shown.

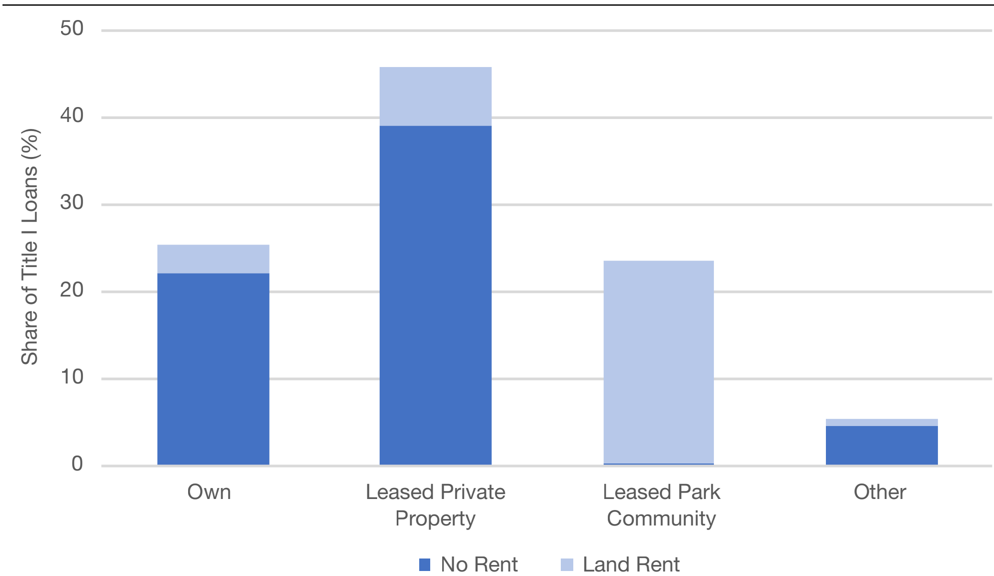
Source: FHA administrative data

The third column further includes the borrower characteristics used in the selection model as covariates. Higher credit scores, higher income, and co-borrowers are associated with a lower risk of default. Minority borrowers are associated with a lower risk of default, whereas older and first-time homebuyers are associated with higher risk. Including those characteristics reduces the hazard ratio associated with Title I to 43 percent; that is, approximately two-thirds of the baseline risk associated with Title I loans (first column) can be explained by the characteristics of the borrowers that program serves. Exhibit 9 illustrates how the cumulative default hazard of 203(b) mortgages increases after matching to Title I borrowers. The fourth column of exhibit 10 introduces new risk factors not included in the selection model. The ratio of required housing payments to income is associated with an increase in the risk of default, but the overall debt-to-income ratio is not statistically significant. The indicator of new construction (fifth column of exhibit 10) is also not significant. Including those risk factors increases the risk associated with Title I.

The sixth column shows the results of including the indicator of paying rent. Roughly one-fourth of Title I borrowers own their land, 46 percent are on leased private property, and only 23 percent are in a mobile home park (exhibit 11). Overall, nearly two-thirds do not pay a lot rent. Title I borrowers without a lot rent payment are associated with a 46-percent increase in the likelihood of default relative to a 203(b) mortgage borrower. Title I borrowers who pay a lot rent are associated with an additional 31-percent increase in default risk, which is statistically significant at the 5-percent level, or 92 percent higher than the risk associated with 203(b) mortgage borrowers. Notably, that estimated effect exists while controlling for the amount of the lot rent, which is incorporated into the housing payment ratio.[9]

Exhibit 11

Title I Land Tenure and Rent



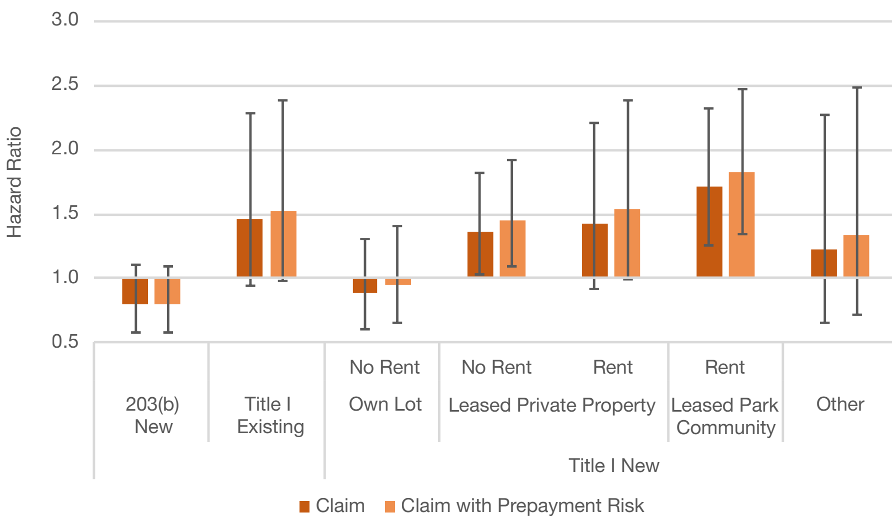
Source: FHA administrative data

[9] The lot rent is the amount at time of underwriting. It does not reflect subsequent changes in lot rent.

The final column of exhibit 10 replaces the lot rent indicator with the land tenure classification. The reference group in the typology is Title I borrowers who own the underlying land. Those borrowers are associated with a 17-percent increase in the likelihood of claim-default relative to 203(b) mortgage borrowers; however, the analysis cannot reject the null hypothesis that the default risk is equivalent to a manufactured home purchase mortgage. Title I borrowers who are on leased private property are associated with a 46-percent increase in the default risk relative to Title I landowners (71 percent relative to 203(b) mortgages), which is significant at the 5-percent level. Title I borrowers in leased park communities are associated with a 79-percent increase in default risk (more than twice the risk of 203(b) mortgages). Exhibit 12 shows the results of an additional specification with select combinations of construction status, lot rent payment, and land tenure type. The results illustrate that Title I landowners are not significantly higher risk than similar homebuyers using 203(b) mortgages, whereas Title I borrowers renting lots in mobile home parks are substantially higher risk.[10]

Exhibit 12

Claim Hazard Ratios



Note: Error bars indicate 95-percent confidence interval.
Source: FHA administrative data

The study used a Cox proportional hazard model to understand the causal effect of property and program type on loan performance (Allison, 2018; Austin, Lee, and Fine, 2016). However, exhibit 13 shows the results of comparable Fine-Gray subhazard models that treat prepayment (i.e., termination without insurance claim) as a competing risk.[11] Title I loans are substantially less likely to prepay, possibly reflecting the difficulty in refinancing personal property loans on manufactured homes (Goodman and Neal, 2021; Russell et al., 2021)—a circumstance that prolongs the exposure of Title I loans to the risk of default. Therefore, the estimated risk associated with Title I loans in the Fine-Gray models shown in exhibit 13 is higher than the comparable estimates

[10] FHA requires a lease of at least 3 years for Title I loans in leased park communities. However, an additional specification (not shown) did not find a statistically significant difference in hazard ratios for such loans before and after 3 years.

[11] Fine-Gray model estimated using the *stcrreg* command in Stata/SE 15.0.

in the Cox models shown in exhibit 10. Nevertheless, the final specification of exhibit 13 and the additional specification in exhibit 12 confirm that Title I landowners are not associated with significantly higher risk than 203(b) mortgage borrowers.

Exhibit 13

Default Hazard with Prepayment Risk

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Title I	3.387***	1.701***	1.561***	1.805***	1.821***	1.571**	1.264
	(0.202)	(0.176)	(0.161)	(0.226)	(0.233)	(0.222)	(0.233)
Credit Score			0.995***	0.996***	0.996***	0.995***	0.996***
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Income (Log)			0.746**	1.106	1.134	1.001	1.090
			(0.082)	(0.195)	(0.208)	(0.187)	(0.205)
Co-Borrower			0.746*	0.667*	0.668*	0.675*	0.679*
			(0.100)	(0.111)	(0.111)	(0.112)	(0.112)
Age			1.016***	1.016***	1.016***	1.015***	1.017***
			(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Race							
African-American			0.708*	0.680*	0.681*	0.689*	0.694*
			(0.112)	(0.109)	(0.109)	(0.110)	(0.111)
Hispanic			0.495*	0.478**	0.478**	0.472**	0.489*
			(0.137)	(0.133)	(0.133)	(0.132)	(0.137)
Other			0.457*	0.439*	0.439*	0.456*	0.445*
			(0.170)	(0.163)	(0.163)	(0.169)	(0.166)
Not Available			0.796	0.791	0.794	0.789	0.792
			(0.194)	(0.196)	(0.196)	(0.195)	(0.196)
First-Time Buyer			1.535***	1.526***	1.523***	1.494***	1.459**
			(0.184)	(0.183)	(0.183)	(0.180)	(0.176)
Housing Ratio				1.021*	1.022*	1.016	1.020*
				(0.009)	(0.009)	(0.009)	(0.009)
Debt Ratio				1.005	1.005	1.005	1.005
				(0.005)	(0.005)	(0.005)	(0.005)
New Construction					0.873	0.888	0.869
					(0.129)	(0.132)	(0.130)
Rent Lot						1.323*	
						(0.164)	
Land Tenure							
Leased Park Community							1.799**
							(0.336)
Leased Private Property							1.449*
							(0.235)
Other							1.662
							(0.962)
Observations	126,775	13,134	13,134	13,134	13,134	13,134	13,134
χ^2	419***	26***	221***	233***	233***	242***	258***
AIC	65,634	14,574	14,429	14,416	14,417	14,412	14,406

AIC = Akaike information criterion.
*Notes: Unemployment rate, manufactured share of housing stock and state and year fixed effects not shown. Statistically significant at the * 0.050 ** 0.010 *** 0.001 level. Robust standard errors shown in parentheses.*
Source: Federal Housing Administration administrative data

Conclusion

Manufactured housing is often seen as a technological solution to the affordable housing problem. The Manufactured Housing Improvement Act of 2000 (Public Law 106-569) states, "[M]anufactured housing plays a vital role in meeting the housing needs of the Nation, and manufactured homes provide a significant resource for affordable homeownership and rental housing accessible to all Americans."[12] FHA is specifically noted as an instrument for improving access to manufactured housing. The 2000 Act calls for a review of FHA's manufactured housing programs and "developing any changes to such programs to promote the affordability of manufactured homes, includes changes in loan terms, amortization periods, regulations and procedures."[13] Eight years later, the FHA Manufactured Housing Loan Modernization Act aimed to "modernize the FHA title I insurance program for manufactured housing loans to enhance participation by Ginnie Mae and the private lending markets." However, a Government Accountability Office (GAO) review in 2014 found that "HUD has not yet examined or researched the effectiveness of these loan programs because its research has focused on other priorities" (GAO, 2014: 29).

This paper compares the performance of personal property insured under Title I with similar mortgages for the purchase of manufactured homes insured under FHA's flagship 203(b) mortgage insurance program. Title I loans are more than three times more likely to default than 203(b) mortgages. However, two-thirds of that difference is because Title I disproportionately serves older, lower-income borrowers with lower credit scores.

The remaining difference is mostly due to land tenure. One-fourth of Title I borrowers own the land on which their manufactured home rests. Those borrowers have approximately the same default risk as 203(b) mortgagors. A plurality of Title I borrowers are on leased private property, and most of them do not pay land rent. Less than one-fourth rent a lot in a mobile home park. FHA requires land leases in park communities to have initial terms of at least 3 years, annually renewable, with 180 days written notice before expiration if the borrower is required to move. Nevertheless, renting land is associated with an increase in the likelihood of default, particularly if in a mobile home park.

There are many challenges to reinvigorating FHA's 50-year-old program of personal property loan insurance for manufactured homes. The maximum loan amount of $69,678 in the Title I program is less than the average cost of a new manufactured home ($81,900 in 2019), not including the costs of transportation and installation. Ginnie Mae places additional requirements for Title I securities issuers compared with issues of securities based on mortgages on single-family homes, limiting the secondary market. Title I continues to rely on manual underwriting and processing of paper case binders.

Title I loans carry a significantly higher interest rate, roughly 2.76 percentage points above the average rate on FHA-insured manufactured home mortgages for otherwise similar borrowers. Higher rates may be expected given the higher risk associated with personal property loans not secured by land. However, FHA provides nearly the same loan-level insurance coverage to Title I

[12] 42 USC § 5401(a).

[13] 42 USC § 5407(a).

loans as to 203(b) mortgages. Investors are reimbursed for 90 percent of losses, and the portfolio limit on claims was removed by the FHA Manufactured Housing Loan Modernization Act of 2008. Therefore, the difference may reflect a more limited secondary market for these loans.

The Manufactured Housing Improvement Act of 2000 encourages the government-sponsored enterprises "to actively develop and implement secondary market securitization programs for the FHA manufactured home loans and those of other loan programs, as appropriate, thereby promoting the availability of affordable manufactured homes to increase homeownership for all people in the United States." The policy goal was reiterated in the Housing and Economic Recovery Act of 2008 (Public Law 110-289), which states that Fannie Mae and Freddie Mac have a "duty to serve" manufactured housing, including developing "loan products and flexible underwriting guidelines to facilitate a secondary market for mortgages on manufactured homes for very low-, low- and moderate-income families." The Act also singles out rural housing markets, where manufactured homes are a greater share of the housing stock. Fannie Mae and Freddie Mac have proposed pilot programs to securitize personal property loans on manufactured homes (Fannie Mae, 2021; Freddie Mac, 2020). However, they currently levy higher fees on manufactured home mortgages; for example, Fannie Mae charges a 50-basis-point upfront charge to purchase mortgages on manufactured homes. Private mortgage insurance can add another 18 to 60 basis points to the monthly cost.

Homeownership without landownership is akin to buying down rent. The upfront cost of buying the housing unit may lower subsequent housing expenses. The potential benefits of this buydown, however, depend on the terms used to finance the purchase and the stability of tenure after purchase. FHA was instrumental in increasing homeownership by popularizing the long-term amortizing mortgage that dominates the American housing finance system. It has an opportunity to play a similar role increasing access to affordable housing by increasing the availability of personal property loans with appropriate risk management and consumer protections.

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Better Housing: FHA Title I Property Improvement Loans

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The views expressed in this article are those of the author and do not represent the official positions or policies of the Office of Policy Development and Research, the U.S. Department of Housing and Urban Development, or the U.S. government.

Abstract

The Federal Housing Administration (FHA) has helped finance home alterations, repairs, and improvements since its creation in 1934. Despite accounting for the majority of FHA-insured loans early in its history, the Title I property improvement program has declined substantially over time. Some of the decline is explained by difficulty regulating the quality of improvement contractors and the growth of conventional financial alternatives but also because Title I loan limits and underwriting procedures have not changed in nearly 30 years. Nevertheless, Title I is still disproportionately used by lower-income borrowers, borrowers with lower credit scores, and borrowers with lower-valued homes. Title I also has a higher share in rural and distressed markets. Reforming the Title I program may help improve the energy efficiency of the residential sector and ameliorate the lack of affordable housing.

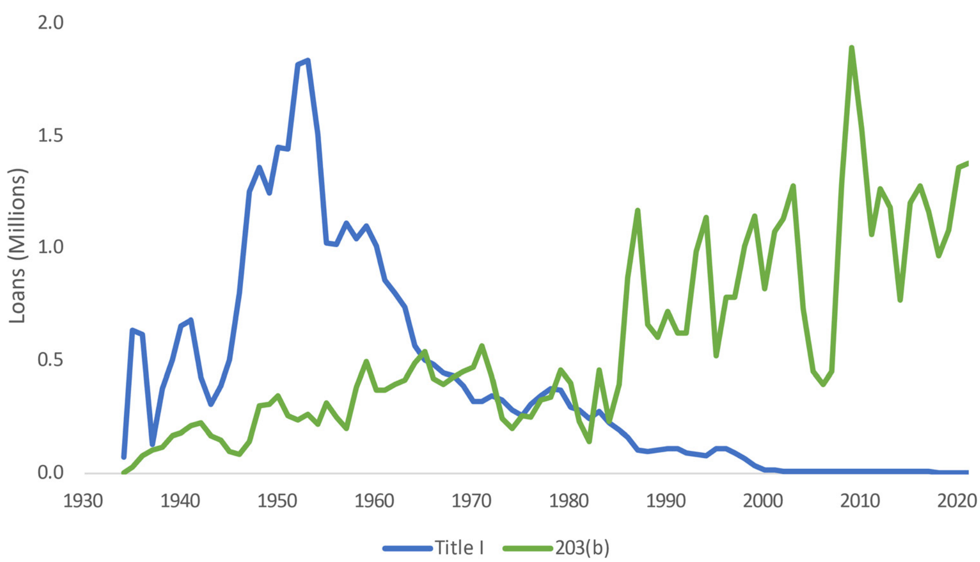
Introduction

The National Housing Act of 1934 is best known for creating the Federal Housing Administration (FHA) to insure home mortgages, but the first section of the Act also covers insurance of financial institutions against losses on loans "for the purpose of financing alterations, repairs, and improvements upon real property." Title I was at the heart of a New Deal initiative to modernize housing as a means to improve the welfare of American households and employ surplus labor in home construction and repair. It also introduced commercial banks to consumer installment lending, which revolutionized household finance.

FHA endorsed more Title I loans per year than home mortgages for its first 35 years (exhibit 1). The cumulative number of property improvement loans was greater than the number of home mortgage program loans until the financial crisis of 2008. Title I, however, is often overlooked (Glock, 2016; Harris, 2009), which may be partly because the property improvement program has not kept pace with changes in the financial industry, causing disbursements to tumble and the program to drift into obscurity.[1]

Exhibit 1

Title I and 203(b) Insured Loan Originations, 1934–2021



Notes: Title I insurance authorization was exhausted in September 1952, creating lending delays. The backlog in disbursements was resolved the following year, resulting in an anomalous spike in Title I loans. The numbers in this chart for those years reflect the loans estimated by FHA based on the daily record of loan report receipts as reported in the 1954 annual report. Loan counts in 1980 and 1981 are imputed on the basis of aggregate dollar volume in those years and the trend in average loan size.

Sources: U.S. Department of Housing and Urban Development. 1980. "1979 Statistical Yearbook"; U.S. Census Bureau. 1987. "Statistical Abstract of the United States: 1988"; U.S. Federal Housing Administration. 1954. "Twentieth Annual Report of the Federal Housing Administration"; U.S. Federal Housing Administration administrative data

Today, home remodeling is a $350 billion market. On average, a homeowner spends $4,120 per year on home maintenance and improvements (Joint Center for Housing Studies, 2021). Most projects are small and can be covered out of pocket, but larger projects require financing. Among projects of at least $50,000, only 54 percent are covered by cash from savings, while extracting home equity through cash-out refinancing and home equity lines of credit accounts for 19 percent of these projects (Joint Center for Housing Studies, 2019). Homeowners with poor credit and limited wealth still need to undertake maintenance and improvements but may be excluded from many financing options.

This article briefly describes FHA's Title I property improvement program and its history. The analysis used data from the Home Mortgage Disclosure Act to examine who Title I still serves.

[1] Title I has also encompassed loan insurance on personal property loans to purchase and refinance manufactured homes since 1969 (Park, 2021). The Title I manufactured housing program is plagued by many of the same problems as the property improvement program, but this article focuses only on the latter.

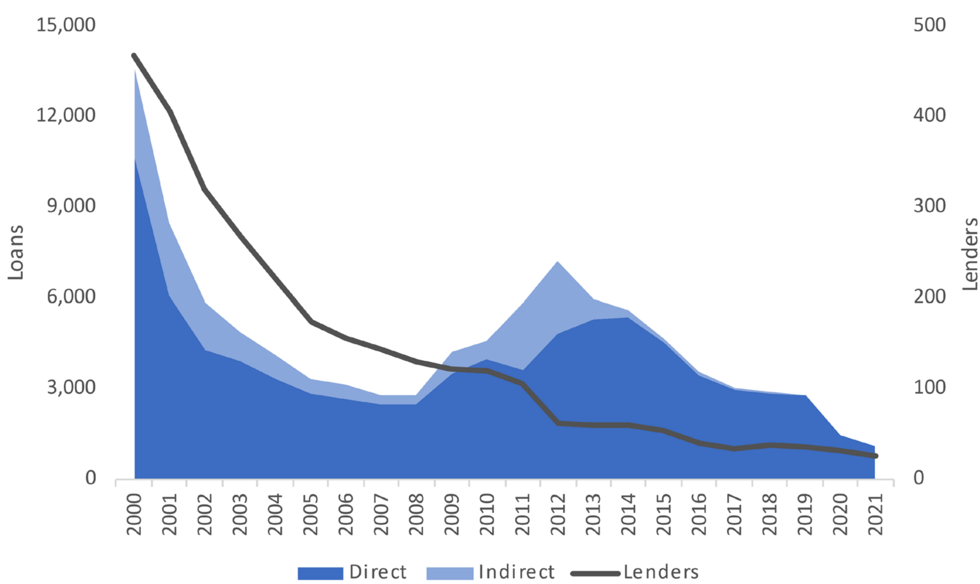
FHA's property improvement loans are disproportionately used by borrowers with lower credit scores and lower-valued homes, by single borrowers (particularly single males), in times and places with high levels of mortgage delinquency, and in rural areas. Those trends suggest that Title I continues to fill a niche in financing property improvements. Reforms of Title I, such as increasing loan limits and automating underwriting to reduce origination costs, could help address needs in the American housing market related to energy efficiency and affordability.

Program Description

After suffering scandals and substantial losses in the 1990s (see section "Suede Shoe Salesmen, Racketeers, and Gangsters" later in this article), FHA reformed the Title I property improvement program. Those reforms helped improve its financial condition but have not stopped a long-run decline in disbursements (exhibit 2). Title I averaged more than 70,000 property improvement loans per year in the 1990s but only 5,000 per year after the year 2000 and even fewer so far in the 2020s. The number of active lenders in the program (i.e., lenders with at least one disbursement in a given year) has declined from more than 1,000 in the 1990s to roughly 30.

Exhibit 2

Title I Lenders and Loan Originations, 2000–2021



Source: Author tabulations of Federal Housing Administration administrative data

Underwriting and Eligibility

Title I lenders must generally meet the same approval requirements as in Title II, which covers the more well-known 203(b) single-family mortgage insurance program. An annual insurance premium of 1 percent of the loan amount is paid by the lender.[2] If the borrower defaults on loan payments, the lender can assign the loan to the U.S. Department of Housing and Urban Development (HUD) for collection through offsets of federal payments (federal tax refunds, Social Security benefits, etc.).

Borrower eligibility is not restricted to residential owner-occupants, but the borrower must have at least one-half interest in the property. Investors and even renters are also eligible if their lease is at least 6 months longer than the loan term. The property can be a single-family or multifamily dwelling, manufactured home (owned as either real or personal property), or even nonresidential.

The property can serve as collateral, or the loan can be unsecured. A property appraisal is not required. No investment, downpayment, home equity, or cash reserves are required. Lenders must pull a credit report from at least two national credit bureaus and analyze the creditworthiness of the borrower, but no minimum credit score is required, and lack of traditional credit history cannot be the sole basis for rejecting an application. Total debt payments as a share of effective income, or the debt-to-income (DTI) ratio, can reach up to 47 percent if compensating factors (e.g., assets after closing, residual income) are present. Loans must be fixed rate, with terms between 6 months and 20 years.[3] The lender must interview the borrower face-to-face or by telephone to ensure that information is complete and accurate.

Loan Limits

One significant factor contributing to the decline of the Title I property improvement program is that loan limits have not kept pace with inflation. The maximum loan amount for a secured home improvement loan was increased from $17,500 to $25,000 for a single-family property (or up to $60,000 for a multifamily property) in September 1992.[4] The maximum unsecured amount was increased from $5,000 to $7,500 in August 1994.[5]

The secured loan limit would have to be doubled ($51,000 for a single-family home) to account for inflation since 1992 (exhibit 3). Home improvement costs have risen faster than overall inflation, however. For example, the Producer Price Index series on Inputs to Residential Maintenance and Repair has increased 159 percent since 1994, which would increase the secured single-family loan limit to $64,700. House prices overall have increased 268 percent, which would increase that limit to $91,900.[6]

[2] Terms fewer than 25 months must be paid upfront, but longer-term loans are paid in annual installments of 1 percent.

[3] Technically, Title I property improvement loans are limited to 20 years and 32 days. Manufactured homes classified as chattel are limited to 12 years and 32 days; manufactured homes classified as real property are limited to 15 years and 32 days. Loan terms of refinances must not exceed the maximum term of the original loan plus 9 years and 11 months.

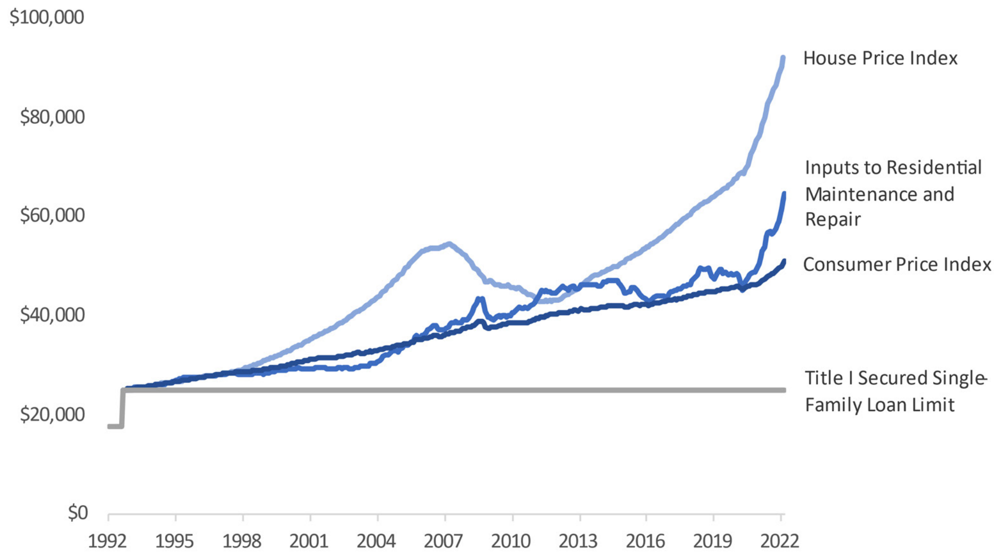
[4] "Increased Maximum Loan Amounts and Loan Terms for Title I Property Improvement Loans." *Title I Letter* 419. September 30, 1992. https://www.hud.gov/sites/documents/TI-419.TXT.

[5] "Major Changes in the Title I Property Improvement and Manufactured Home Loan Programs." *Title I Letter* 428. July 22, 1994. https://www.hud.gov/sites/documents/TI-428.TXT.

[6] If one were to index the original loan limit of $2,000 in 1934 to inflation, the current limit would be $43,560, or up to $126,800 to account for house prices using Shiller's (2022) historical house price index.

Exhibit 3

(Price-Adjusted) Title I Secured Single-Family Loan Limit

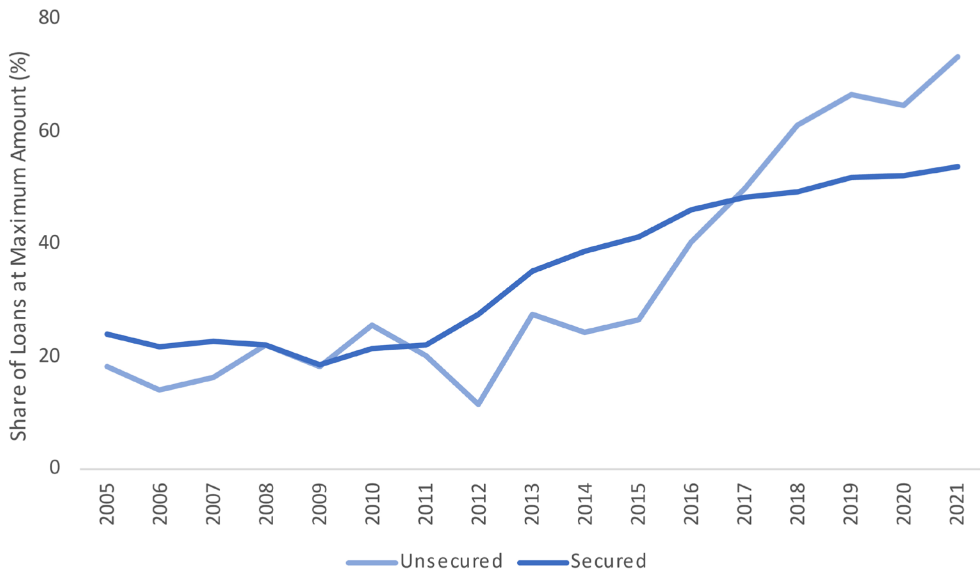


Source: U.S. Bureau of Labor Statistics; U.S. Federal Housing Finance Agency

Evidence shows that failing to increase loan limits has made them more binding over time. The share of single-family loans for the maximum loan amount has doubled from less than one-fourth in 2012 to more than one-half by 2018, including nearly three-fourths of unsecured loans by 2021 (exhibit 4). The increase in the share of loans at the maximum loan amount corresponds to the declining number of Title I disbursements and market share.

Exhibit 4

Share at Maximum Loan Amount, 2005–2021



Source: Author tabulations of Federal Housing Administration administrative data

Reserve Account

Unlike FHA's standard loan insurance programs, Title I property improvement loans are financed through a system of co-insurance. The insurance covers 90 percent of loan losses but cannot exceed a Reserve Account equal to 10 percent of the aggregate amount disbursed by a lender. The risk-sharing arrangement in Title I is meant to limit FHA's liability and align incentives. A lack of "skin-in-the-game" by lenders creates a moral hazard that undermines rigorous underwriting and was seen as a substantial contributor to the financial crisis of 2008, particularly in the private securitization market (Keys et al., 2010; Levitin and Wachter, 2012; Mian and Sufi, 2008). Consequently, the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010[7] requires risk retention except for loans meeting a prescribed definition of low risk.

The portfolio structure of the co-insurance can also distort incentives. As defaults increase, lenders have an incentive to originate more loans to increase the Reserve Account. That moral hazard may have contributed to a high level of defaults and claims in the 1980s and 1990s, particularly in FHA's Title I manufactured housing program, which had a similar co-insurance scheme. The FHA Manufactured Housing Loan Modernization Act of 2008[8] converted Title I manufactured home loans to a loan-level insurance similar to Title II to encourage loan securitization. However, Title I property improvement loan insurance retains aggregate limits.

[7] Public Law 111-203.

[8] Part of the Housing and Economic Recovery Act, Public Law 110-289.

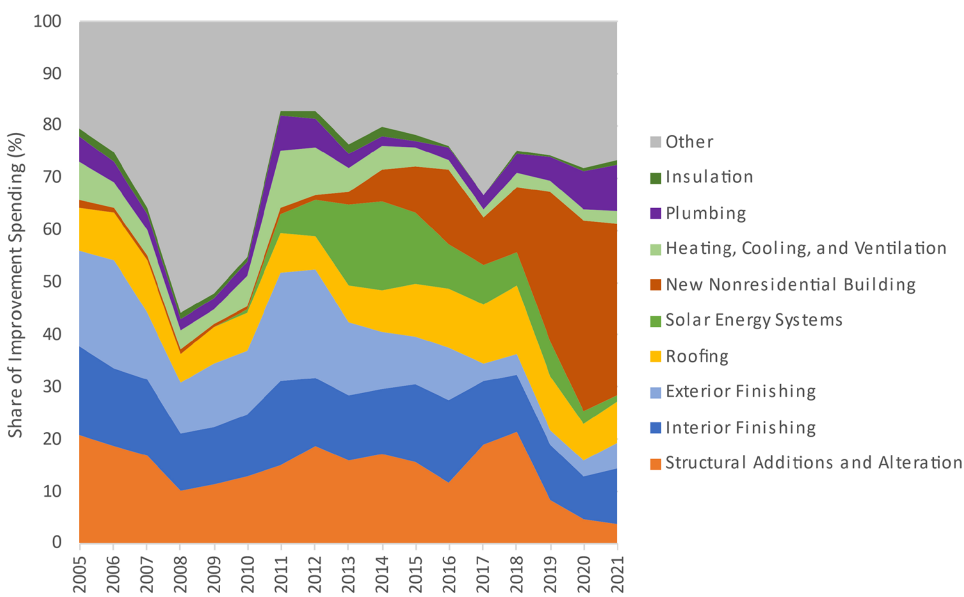
Types of Improvements

The nature of the improvements to be made must be specified, and the lender must determine if all improvements are eligible for Title I financing as well as the reasonableness of the costs for labor and materials. Improvements must substantially protect or improve the basic livability or utility of the property, generally must be permanent, and may not include components not fully owned by the borrower (e.g., leased energy systems). Loan proceeds may only be used for improvements started after loan approval, although an exception may be made for presidentially declared disaster areas.

Between 2005 and 2022, $1.04 billion in Title I property improvement loans (excluding refinances) financed $1.48 billion in property improvements. That is, actual improvement spending is roughly 42 percent higher than the amount borrowed, or the loan amount covers about 70 percent of expenditures. Exhibit 5 shows what types of improvements are financed by Title I. The most common types of improvements are structural additions and alterations, accounting for 15 percent of Title I-financed improvements, followed by interior and exterior finishing (roughly 13 percent each) and roofing (8 percent). Solar energy systems account for less than 6 percent of expenditures over the entire period but reached as high as 17 percent in 2014. More recently, expenditures for new nonresidential buildings have risen from less than 1 percent of Title I-financed improvements to over 30 percent, albeit of a declining amount of total Title I disbursements.

Exhibit 5

Title I-Financed Home Improvements



Source: Author tabulations of Federal Housing Administration administrative data

Unsecured loans accounted for only 7 percent of the total disbursed loan amount, but 13 percent of improvement spending, because the ratio of expenditures to borrowing was nearly 2.7 (compared with only 1.3 for secured loans). Unsecured loans were more likely used for exterior finishing (17 percent), heating, cooling, and ventilation (13 percent), interior finishing (13 percent), and structural additions and alterations (11 percent).

History

This section briefly describes the origins of FHA's property improvement program, the persistent problem of unscrupulous lenders and contractors, and an attempted reform to promote energy efficiency.

A Curious Duality of Objective

The goal of the Title I program was ostensibly the modernization of American homes, but an underlying motive was stimulating the home construction industry and associated manufacturers amid the Great Depression. In doing so, FHA helped revolutionize the relationship between households and financial markets. Similar to how FHA's 203(b) program made the long-term, fully-amortizing home mortgage with a low downpayment the American standard, the Title I program helped popularize consumer installment credit.

Consumer credit markets are often plagued by imperfect information. Assessing the creditworthiness of thousands of individual customers and monitoring their repayment is substantially more costly than maintaining relationships with large businesses over many repeated transactions. Consequently, consumer credit is rationed (Stiglitz and Weiss, 1981). Credit bureaus were created for retailers and manufacturers to overcome this market failure by sharing information on borrowers. For example, Equifax was founded as the Retail Credit Company in 1898 by two grocers who started selling their list of creditworthy customers to other companies. Nevertheless, commercial banks typically avoided the trouble and perils of consumer lending altogether until the early 20th century (Hyman, 2011). Alternative financial institutions tried to bridge the gap between commercial banks and loan sharks using forms of joint liability. “Morris Plan” banks first appeared in 1910 and required cosigners to vouch for the creditworthiness of the borrower and assume the risk of default. More broadly, the concept of credit unions as member-owned financial cooperatives, often based around a common interest such as a trade union, was imported from Germany (Muchinski and Phillips, 2008). The first credit union in the United States, St. Mary's Cooperative Credit Association, was created in 1909. Many of these institutions first offered borrowers installment loans, in which a fixed amount of money is borrowed and repaid in regular payments, frequently without collateral.

Manufacturers, particularly automobile companies, also pioneered this new form of credit, often creating their own subsidiary financial companies. General Motors created the General Motors Acceptance Corporation (GMAC) in 1919 to provide wholesale financing for dealers, but they increasingly turned to retail financing for consumers by the mid-1920s. “Modern, pervasive installment credit found its institutional bedrock in the financial innovation of the early automobile industry” (Hyman, 2011: 21). Home appliance manufacturers created similar finance arrangements. American Radiator created the Heating and Plumbing Finance Corporation in

1926. Johns-Mansville, a manufacturer of insulation and roofing material, aggressively marketed its “Million Dollars to Lend” for both its own goods and others. Sears, Roebuck and Co. offered loans of $50 or more for home improvement, requiring a 10 percent downpayment and 8 percent interest repaid over 2 years (Harris, 2012). More typically, property improvement loans required a downpayment of 12 to 20 percent and carried interest rates between 18 and 25 percent, repaid over a period of 12 months (McFarland, 1947). By the end of the decade, consumer loans financed large majorities of furniture, radio, and automobile purchases (Harris, 2009).

Home “modernization” was promoted by civic organizations. Better Homes in America, headed by then-Commerce Secretary Herbert Hoover, was created not only to encourage the production of “sound, beautiful, single-family houses” but also to “encourage the reconditioning and remodeling of older houses” using the latest in building technology and modern appliances (Better Homes in America, 1925). When Hoover became president, he convened the President’s Conference on Home Building and Home Ownership in 1930. The conference promoted the role of property improvement in protecting financial investment, influencing family character, improving family welfare, and upholding community standards. “National well-being is in part indicated by the progress made in the reconditioning, remodeling, and modernization of homes.” (Gries and Ford, 1932: 224).

In the middle of the Great Depression, the conference also acknowledged the economic stimulus of home improvement spending. “[P]ossibilities exist in many communities for creating additional opportunities for employment and for stimulating business in certain lines through development of activity in connection with reconditioning, remodeling, and modernizing of homes. While such work increases employment for workers, it also tends to increase buying power generally, and stimulates sales of materials and services in the construction and allied fields.” (Gries and Ford 1932: 226). By the time the conference report on “Home Repair and Remodeling” was published in 1932, more than 12 million Americans were unemployed, accounting for nearly one-quarter of the civilian workforce (Lebergott, 1948). However, “government” was not listed as a party that should promote home improvement.

In contrast, President Roosevelt’s administration took a more active approach. The Home Owners’ Loan Act of 1933[9] allowed the Home Owners’ Loan Corporation (HOLC) not only to refinance mortgages but also “in connection with any such exchange, to make advances in cash … to provide for necessary maintenance and make necessary repairs.” This program was expanded to include reconditioning loans for “maintenance, repair, rehabilitation, modernization, rebuilding, and enlargement.”[10] “The dominant objective of this liberalization appears to have been to stimulate the construction industry and business generally, but other ends were sought as well: to provide more aid to home owners, to improve the security for HOLC loans, and possibly to aid in making properties more nearly self-supporting by the addition of income-producing features” (Harriss, 1951: 128). Roughly $5 million was advanced for maintenance and $71 million was loaned to over 361,000 homes (Harriss, 1951).

[9] Pub. L. 73-43, 48 Stat. 128.

[10] 48 Stat. 643, 1934.

Building on the HOLC, the National Housing Act of 1934[11] created FHA to insure new home mortgages and property improvement loans. A key concept of FHA is leveraging private investment through government guarantees in order to stimulate the economy. Marriner Eccles, whom Roosevelt would appoint as chair of the Federal Reserve, outlines the program and describes the Keynesian[12] logic of stimulating private investment.

> What was to be the first part of the act, or Title I, addressed itself to the modernization of homes and businesses. The details of the program represented a union between Albert Deane's practical knowledge of the costs of consumer credit and the scheme I advanced to finance that credit. In general terms, the amount of credit that could be authorized was limited to two thousand dollars for each loan. No collateral was required by an applicant for these loans. He was to be granted one on the strength of his character and job prospects alone, as judged by the local lending institution with which he dealt.
>
> Throughout the whole economy the confidence of lending institutions in the credit scheme was to be bolstered by the federal government, which stood ready to absorb losses up to twenty per cent of the aggregate loans that were made by any one institution that qualified as a lending agency. In precise terms, the government could absorb losses up to $200 million. But unlike a relief appropriation of a like amount, the $200 million subsidy in this case would draw into the spending stream $1 billion of private funds. This short-run emergency measure would have the lasting effect of adding to the value of existing properties at a time when debtors got the greatest benefit from their expenditures. This needless to say, is the safest condition under which one could go into debt. (Eccles 1951: 149–150)

The Title I program was modeled on Johns-Manville's home improvement plan. Albert Deane, president of GMAC, served as Deputy FHA Commissioner overseeing the program.

Leveraging private capital was meant to multiply the effectiveness of government spending in stimulating the economy. Former Assistant FHA Commissioner Carter McFarland (1947), writes, "Like other federal legislation of the period affecting housing, Title I is characterized by a curious duality of objective. It was not only a program designed to improve housing standards and conditions; it was also a part of the federal government's fiscal policy designed to influence the volume, terms and maturities of credit extended to finance real property and, thereby, to stimulate employment. If anything sets Title I apart from other federal housing legislation it is the fact that even more emphasis than usual was placed on the fiscal aspects of the plan, even less on its implications for housing." Similar to how manufacturers promoted installment credit to bolster sales, the federal government promoted installment credit to boost the economy more generally.

[11] Pub. L. 73-479, 48 Stat. 1246.

[12] Eccles denies being directly influenced by Keynes. "[T]he concepts I formulated, which have been called 'Keynesian,' were not abstracted from his books, which I have never read" (Eccles, 1951: 132).

Highlighting its simulative purpose, Title I insurance was initially free to lenders who followed its regulations. Not until 1939 was an insurance premium levied to cover expenses.[13] FHA's insurance covered the full loan amount but was limited to 20 percent of the aggregate insured loan volume disbursed by a lender. This was lowered to 10 percent in 1936.[14] Coverage was capped at 90 percent of the loan amount in 1954.[15] Amendments in 1936 extended eligibility from property owners to lease holders as long as the lease extended at least 6 months beyond the loan maturity date. The maximum interest rate was equivalent to 9.72 percent, less than half the prevailing rate. Loan terms averaged 30 months but could be up to 5 years, and no downpayment or collateral was required (McFarland, 1947).

Original authorization for the Title I program lapsed in 1937. In that time, FHA insured over 1.45 million property improvement loans for a total of $560.6 million (FHA, 1938). FHA, moreover, claimed Title I did not substantially displace existing credit but actually expanded home improvement financing. "From a questionnaire submitted to institutions extending the major portion of these loans, it was ascertained that practically all modernization loans originated solely because of the existence of the plan. This is therefore new additional credit" (FHA, 1935: 8). "Title I contributed to the establishment of conditions favorable to an expansion of installment credit in the field of property improvement. From those considerations we are justified in deducing that a large proportion of Title I loans represented installment loans for property improvement that would not otherwise have been made" (McFarland, 1947: 411). In addition, property improvement loans favored the rehabilitation of the existing housing stock in urban areas over new construction in the suburbs. "The vast majority of Americans who experienced the FHA in the 1930s, '40s and '50s thus experienced it as an agency that financed old housing in need of repair and not new tract housing in the suburbs" (Glock, 2016: 304).

FHA only accounted for 2 to 3 percent of outstanding consumer installment credit in the United States in the 1930s. Nevertheless, "The fact that the federal government was sponsoring a consumer loan program involving such relatively liberal terms must have played its part in sanctioning liberality of financing in other fields" (McFarland, 1947: 408). This included national banks, which had traditionally avoided consumer credit but accounted for 44 percent of Title I dollar volume (FHA, 1938). "The principal contribution of FHA would seem to be its achievement of what Administrator McDonald called 'the big thing'—the education of commercial bankers with regard to small character loans amortized on a monthly repayment basis" (Coppock, 1940: 5).

Title I was reauthorized in 1938, and FHA annually endorsed more property improvement loans than home mortgages until the 1960s. A HUD-commissioned report in 1977 proclaims, "The Title I program has been a popular and successful endeavor … Title I stands out as a model for federal-private cooperation" (Foden, Dubinsky, and Hass, 1977: 14). "Deane's success showed what could be done by a person who understood fully what the legislation was meant to do, who was in sympathy with its objectives and was willing to take the hustings and advertise the prospect

[13] Pub. L. 76-111.

[14] Pub. L. 74-486.

[15] Pub. L. 83-560.

the measure opened to all who owned homes and businesses and needed credit for repairs and improvements.“ (Eccles, 1951: 159).

Suede Shoe Salesmen, Racketeers, and Gangsters

Title I property improvement loans were rarely disbursed directly to the borrower. “Instead the institution most commonly paid the amount borrowed directly to the building contractor or to the seller of equipment with whom the borrower dealt” (Coppock, 1940: 25–26). McFarland (1947) states that 80 percent of loans originated through dealers.

Unfortunately, indirect disbursements deprive the borrower of leverage to ensure that property improvements are completed satisfactorily. Unscrupulous contractors can promise improvements only to abscond with the money, leaving the borrower saddled with debt and shoddy or unfinished work. Writing in FHA’s journal, *Insured Mortgage Portfolio*, Bushman (1945) laments,

> Unfortunately there is a bad class of dealers. While their number is relatively small, the damage they do is disproportionately large. They exist by virtue of lending institutions which are so insatiably hungry for volume that they solicit and accept business without discrimination as to the source and without regard for injury to their own reputation. It must be admitted, with regret, that some banks are among the worst offenders.
>
> These dealers treat Title I as a racket. They look like racketeers, act like racketeers, and use the jargon of racketeers … Dealers and salesmen of this type are floaters, usually going from city to city wherever they hear that the lending institutions are hungry and wide open. Usually they evacuate a territory when the FHA or the district attorney start checking up. Their stock in trade is a smooth tongue and a complete lack of conscience. They will promise anything to make a sale (but not in writing) and their price for a job is limited only by the gullibility of the buyer. They cheat on the price, they cheat on the job, and they cheat on the institutions. (Bushman, 1945: 28)

Dealer loans continued to account for three of four Title I loans in the 1950s (Foden, Dubinsky, and Hass, 1977). The problems with disreputable contractors persisted, however. In a 1955 congressional hearing, Senator Homer Capehart, the Chairman of the Senate Committee on Banking and Currency, rails,

> Over the years ‘suede-shoe salesmen’ and ‘dynamiters’ whose ranks have included racketeers and gangsters have infiltrated this business. They have used fraudulent and deceptive sales practices on thousands of homeowners … Most home repair contractors are both honest and reliable. But the laxity in the administration of the Title I program enabled dishonest people to make illicit profits from owners of small homes who perhaps could least afford the losses.

Foden, Dubinsky, and Hass (1977) attribute declining Title I volume to lower demand for home improvement financing and growth of conventional alternatives, but also doubtful households and reforms designed to curb fraud. "In the early fifties, dealer abuses were brought to light, and stricter regulations were enacted to prevent them from recurring. This was a major contributor to a precipitous decline in Title I loans, as doubtful dealer loans were excluded from the program, both because of the new Title I regulations and because of the wariness with which lenders began to view the remodeling industry and dealer lending" (Foden, Dubinsky, and Hass, 1977: 14).

Indirect disbursements continued to account for roughly one-half of Title I improvement loans in the early 1990s. Concerns with dishonest contractors also continued, however. Between 1987 and 1994, the claim rate on dealer loans was 6 percent, compared with 3.5 percent for direct loans (HUD 1997). HUD's inspector general recommended prohibiting dealer loans in 1986, 1995, and 1997.[16] A series in *The Philadelphia Inquirer* documented numerous incidents of shoddy work at inflated prices (Fazlollah and Phillips, 1998a; 1998b; Fazlollah, 2002). An investigation by the Government Accountability Office (1998) found HUD collected limited information on borrower, loan, and property characteristics and conducted limited oversight of program compliance. HUD completed on-site lender reviews of only 2 out of roughly 3,700 lenders in fiscal year 1997. More than one-half of insurance claims lacked required documents, including underwriting information and improvement completion certificates.

Subsequent reforms sharply reduced dealer loans. Direct disbursements to dealers only were banned in 2001, although joint disbursements to borrowers and dealers continue. In addition, lenders are required to confirm with the borrower that the work has been satisfactorily completed.[17] Aside from a spike in indirect loans in 2011 and 2012 related to a single lender, dealer loans have been almost driven out of the Title I program.

PowerSaver Pilot: Retrofit Redux

In October 2009, the Obama administration released the *Recovery through Retrofit* report, which noted that the residential sector is responsible for one-fifth of the nation's carbon dioxide emissions. Existing techniques and technology could reduce home energy use by 40 percent, lower greenhouse gas emissions by 160 million metric tons per year, and save consumers $21 billion annually on energy bills. Households face barriers to modernizing their homes, however, including access to financing. "Homeowners face high upfront costs and many are concerned that they will be prevented from recouping the value of their investment if they choose to sell their home. The upfront costs of home retrofit projects are often beyond the average homeowner's budget" (Middle Class Task Force, 2009: 1). The Consolidated Appropriations Act of 2010[18] included $50 million for an Energy Innovation Fund, of which one-half was for an Energy Efficient Mortgage Innovation pilot program for single-family homes. In response, HUD modified the Title I property improvement program to include a new "PowerSaver Home Energy Retrofit Loan Pilot Program."

[16] Kulh-Inclan, Kathryn. 1998. Testimony before the U.S. House of Representatives, Committee on Banking and Financial Services, Subcommittee on Housing and Community Opportunity. Hearing on Consumer Abuses in Home Improvement Financing, April 30.

[17] "Publication of Final Rule on November 7, 2001 Regarding: Strengthening the Title I Property Improvement and Manufactured Home Loan Insurance Programs and Title I Lender/Title II Mortgagee Approval Requirements," *Title I Letter* 473. November 7, 2001. https://www.hud.gov/sites/documents/ti-473.doc.

[18] Pub. Law 111-117.

FHA's stated goals for the pilot were

> (1) To facilitate the testing and scaling of a mainstream mortgage product for home energy retrofit loans that includes liquidity options for lenders, resulting in more affordable and widely available loans than are currently available for home energy retrofits; and (2) to establish a robust set of data on home energy improvements and their impact—on energy savings, borrower income, property value, and other metrics—for the purpose of driving development and expansion of mainstream mortgage products to support home energy retrofits.[19]

Eligibility was limited to owner-occupants of single-family homes. Initially, eligibility was geographically limited to selection locations that "have already developed a robust home energy efficiency retrofit infrastructure," but this restriction was lifted in September 2013.[20] Improvements had to improve home energy performance or directly make such measures possible. Loans were disbursed in increments, one-half at loan closing and one-half after the property improvements were completed. Initially, the combined value of existing mortgages and the property improvement loan could not exceed 100 percent of the house value as determined by an exterior appraisal; however, this requirement was subsequently repealed. Loan terms were limited to 15 instead of 20 years, except for certain approved improvements. A minimum credit score of 660 was required. The maximum debt-to-income ratio was 45 percent.

Appropriations were used to fund lender incentives, including lowering interest rates and reducing servicing costs. Grants ranged from $140,000 to $2.7 million. Dealer loans were initially not permitted. "The reason for this limitation is that dealer loans have been disproportionately correlated with poor loan performance under Title I and other home improvement loan programs in the past. While HUD recognizes that there are many responsible dealers who can and would provide financing through dealer loans in a responsible manner, it is limiting the Retrofit Pilot Program to 'direct loans'".[21] The dealer loan ban was later lifted despite this reasoning.

More than 900 loans totaling roughly $9 million were disbursed under the PowerSaver program between September 2011 and July 2015. These loans financed almost $14.9 million in property improvements, particularly heating, cooling, and ventilation systems (34 percent), insulation (30 percent), and solar energy (13 percent). As of April 2022, only 9 loans had defaulted, resulting in cumulative claims of less than $33,900 (prior to debt collection) compared with nearly $392,000 in premium revenue.

The PowerSaver program was unable to gain greater popularity for many of the same reasons that have led the Title I program to decline. Low loan limits limited interest from large national lenders, and existing Title I lenders did not participate because of additional program requirements (e.g., appraisals). Lenders suggested raising loan limits generally and lowering insurance premiums for energy efficiency improvements to increase product uptake.

[19] 75 FR 69113.

[20] "Modifications to the Home Energy Retrofit Loan Pilot Program (FHA PowerSaver Pilot Program)." *Title I Letter* 485. September 18, 2013. https://www.hud.gov/sites/documents/TI-485.PDF.

[21] 75 FR 69117.

Market Share

This section compares FHA-insured improvement loans with other forms of home improvement financing to better understand who relies on Title I.

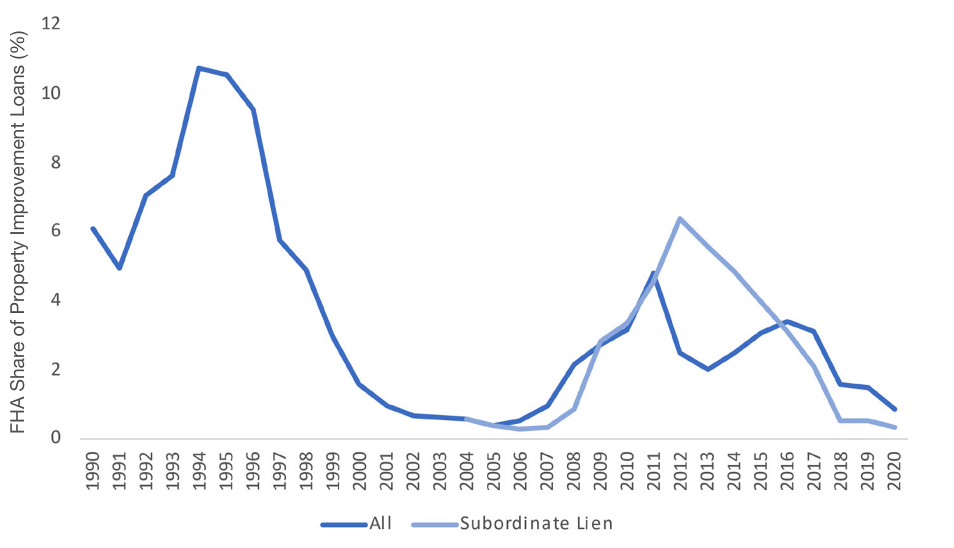
Data

Information on FHA-insured and other property improvement loans is collected under the Home Mortgage Disclosure Act (HMDA). Loans in HMDA will only be reported as property improvement loans if they are not purchase or refinance loans.[22] This study focused specifically on subordinate liens on one- to four-unit dwellings (including manufactured homes) because most Title I loans are subordinate liens, and this helps to avoid confusion with FHA's 203(k) rehabilitation mortgages, which may also be reported as first lien home improvement loans in HMDA. Some unsecured loans used to be reported under HMDA, but a 2015 rule from the Consumer Financial Protection Bureau adopted a "dwelling-secured standard."[23]

Exhibit 6 shows FHA's share of property improvement loan originations reported in HMDA. Consistent with the trend in the number of Title I loans, FHA's market share declined precipitously in the late 1990s. Subordinate liens can be identified in HMDA starting in 2004 and show a peak of more than 6 percent in 2012 before falling to less than 1 percent by 2018.

Exhibit 6

FHA Subordinate Lien Improvement Loans Market Share, 1990–2020



Source: Home Mortgage Disclosure Act

[22] "If a covered loan is a home purchase loan as well as a home improvement loan, a refinancing, or a cash-out refinancing, an institution complies with § 1003.4(a)(3) by reporting the loan as a home purchase loan. If a covered loan is a home improvement loan as well as a refinancing or cash-out refinancing, but the covered loan is not a home purchase loan, an institution complies with § 1003.4(a)(3) by reporting the covered loan as a refinancing or a cash-out refinancing, as appropriate." 12 CFR 1003.4(a)(3) Comment 3.

[23] "The final rule excludes from coverage home improvement loans that are not secured by a dwelling" (RIN3170-AA10: 3).

Exhibit 7 provides descriptive statistics comparing recent Title I loans in FHA's administrative data with FHA-insured subordinate lien property improvement loans and other home improvement financing options as reported in HMDA. The number of loans reported in HMDA is slightly fewer than in the administrative data, which is expected given exceptions to required disclosures. In addition, the average loan amount, income, and credit score are slightly higher. It is nevertheless clear that Title I loans are more likely to be relied on by lower-income borrowers with lower credit scores and lower property values than alternative financing options.

Exhibit 7

Descriptive Statistics, 2018–20

	Title I Property Improvement		HMDA				
	All	Subordinate Lien	FHA Subordinate Improvement	Other Subordinate Improvement	First Lien Improvement	HELOC	Cash Out Refinance
Loan Amount	$17,234	$19,046	$19,491	$44,036	$161,431	$104,203	$241,127
	(6,438)	(4,960)	(7,583)	(45,081)	(213,259)	(129,290)	(211,688)
Monthly	$5,642	$5,867	$7,825	$9,479	$7,573	$10,403	$8,475
Income	(3,131)	(3,135)	(4,047)	(6,246)	(6,725)	(8,609)	(6,733)
Missing	0.0%	0.0%	0.3%	1.6%	2.9%	2.2%	1.7%
Credit Score	719	719	729	748	738	767	732
	(54)	(53)	(51)	(57)	(60)	(52)	(54)
Missing	8.4%	7.8%	3.8%	14.7%	14.2%	1.7%	4.6%
Property Value			$224,557	$321,451	$321,537	$420,005	$386,180
			(125,988)	(219,193)	(292,463)	(359,817)	(302,971)
Missing	100.0%	100.0%	67.7%	12.7%	12.8%	0.3%	4.1%
Race/Ethnicity							
White	82.1%	82.1%	76.9%	70.6%	67.7%	71.4%	61.7%
Hispanic	4.0	4.2	3.9	5.0	6.6	3.6	6.2
Black	6.6	6.3	5.4	3.6	4.3	2.8	4.1
Other	4.3	4.5	5.6	7.2	6.2	8.5	7.3
Not Reported	3.1	2.8	8.2	13.6	15.3	13.7	20.7
Gender							
Co-Borrowers	48.9%	50.2%	49.8%	56.4%	47.0%	55.7%	48.8%
Single Male	34.4	34.0	33.5	24.7	27.0	24.6	27.4
Single Female	16.8	15.8	15.8	16.0	21.3	16.4	18.6
Not Reported	0.0	0.0	0.9	2.9	4.7	3.3	5.2
Loans	7,033	5,915	5,037	231,258	115,856	189,596	222,982

FHA = Federal Housing Administration. HELOC = home equity line of credit. HMDA = Home Mortgage Disclosure Act.
Notes: Excludes 93 Title I refinances. Dollars adjusted for inflation to 2022 values. Standard deviations shown in parentheses.
Source: Author tabulations of Federal Housing Administration administrative data

Methodology

This study used logistic regressions to estimate the likelihood of using FHA-insured property improvement loans. First, this analysis compared only FHA and all other subordinate lien property improvement loans between 2007 and 2020 using a binomial logistic regression. However, subordinate liens are not the only method of financing improvements. Borrowers may also obtain first lien property improvement loans as well as extract equity through refinancing. Therefore, this analysis also estimated a multinomial logistic regression,

$$P(Y = K) = \frac{e^{\beta_{K-1}X}}{1 + \sum_{k}^{K-1} e^{\beta_K X}}$$

where

$$k \begin{cases} 0 & \text{Subordinate Other Property Improvement Loan} \\ 1 & \text{Subordinate FHA Insured Property Improvement Loan} \\ 2 & \text{First Lien Property Improvement Loan} \\ 3 & \text{Refinance Loan} \end{cases}$$

and X represents economic conditions and borrower-level characteristics described below.

Beginning in 2018, home equity lines of credit can be distinguished from closed-end property improvement loans, and refinances that extract equity can be distinguished from other refinances. This differentiation allows a refined and expanded classification of financing options.

$$k \begin{cases} 0 & \text{Subordinate Other Closed-End Property Improvement Loan} \\ 1 & \text{Subordinate FHA-Insured Closed-End Property Improvement Loan} \\ 2 & \text{First Lien Closed-End Property Improvement Loan} \\ 3 & \text{Home Equity Line of Credit} \\ 4 & \text{Closed-End Cash-Out Refinance Loan} \end{cases}$$

This study used the following borrower-level characteristics to estimate the likelihood of using a particular financing option.

Income	The natural logarithm of borrower income adjusted for inflation. Non-missing values are Winsorized[24] to limit the influence of outliers. Missing income is stochastically imputed using a regression of available reported income on county-level per capita income with state and year fixed effects. A binary variable indicates loans with imputed income.
Credit Score	A numeric indicator of creditworthiness typically ranging between 300 and 850. These data have been available in HMDA since 2018.
Property Value	The natural logarithm of property value adjusted for inflation. Non-missing values are Winsorized to limit the influence of outliers. These data have been available in HMDA since 2018.

[24] Winsorization refers to top- and bottom-coding values at given percentiles. In this case, the top and bottom one percent of income and property values are replaced with 99th and 1st percentiles, respectively.

Race/Ethnicity	A categorical variable indicating whether the borrower (and co-borrower, if applicable) are: non-Hispanic White, Hispanic (any race), non-Hispanic Black, other or two or more races/ethnicities, or race/ethnicity not reported.
Gender	A categorical variable indicating whether the borrowers are: single male, single female, not reported, or more than one borrower.

This research accounted for the interest rate environment that may affect whether a homeowner refinances their primary mortgage rather than obtain a subordinate property improvement loan.

Interest Rate	The median interest rate on an FHA-insured home purchase loan in that month.
Change in Rates	The percentage point change in the median interest rate over the previous 12 months.

This analysis also accounted for county-level economic conditions that may affect the type of credit available.

Application Rate	The number of home purchase mortgage applications in the previous 12 months computed using data from the Home Mortgage Disclosure Act per thousand owner-occupied housing units reported in the 2010 Decennial Census.
Denial Rate	The share of all home purchase mortgage applications denied by lender in previous 12 months computed using data from the Home Mortgage Disclosure Act.
FHA Share	The share of FHA insurance among purchase mortgages originated in the previous 12 months computed using data from the Home Mortgage Disclosure Act.
Unemployment	The average unemployment rate in the previous 12 months reported by the Bureau of Labor Statistics.
Change in Jobs	The percent change in employment over the previous 12 months.
Delinquency Rate	The average share of mortgages 90-days or more delinquent, including foreclosure, in the previous 12 months reported by CoreLogic.
Sales Price	The average price of houses sold in the previous 12 months reported by CoreLogic.
Price Appreciation	The percent change in CoreLogic's single-family house price index over the previous 12 months.
RUCC	The Rural-Urban Continuum Classification of counties by the U.S. Department of Agriculture.

Fixed effects for year and Census Division are also included.

This study used a stratified random sample of the HMDA data in order to facilitate computation. The following sampling rates were applied to the different loan types in the 2007 to 2020 sample.

Subordinate Other Property Improvement Loan	10.0%
Subordinate FHA Insured Property Improvement Loan	100.0%
First Lien Property Improvement Loan	5.0%
Refinance Loan	0.5%

This method created a sample of nearly 680,000 loans. The following sampling rates were applied to the refined and expanded loan type categories in the 2018 to 2020 sample.

Subordinate Other Closed-End Property Improvement Loan	100.0%
Subordinate FHA-Insured Closed-End Property Improvement Loan	100.0%
First Lien Closed-End Property Improvement Loan	50.0%
Home Equity Line of Credit	10.0%
Closed-End Cash-Out Refinance Loan	5.0%

This method created a second sample of roughly 759,000 loans. Weights were applied to account for the differences in sampling rates.

Findings

Exhibit 8 presents the results using loan originations between 2007 and 2020. The first three columns show the results of the binomial logistic regression comparing only FHA-insured loans to all other subordinate lien home improvement loans. The last three columns show the same comparison but account for the availability of first lien improvement loans and refinances using a multinomial logistic regression. Exhibit 9 similarly presents the results of a multinomial logistic regression using only 2018 to 2020 originations, comparing FHA-insured loans to other closed-end subordinate lien improvement loans while accounting for the availability of closed-end first lien improvement loans, home equity lines of credit, and cash out refinances. Full results are available in an appendix.

Exhibit 8

Odds of FHA Relative to Other Subordinate Lien Improvement Loans, 2007–20

	Binominal Results			Select Multinomial Results		
	(1)	(2)	(3)	(4)	(5)	(6)
Income (Log)	0.747***	0.747***	0.762***	0.737***	0.738***	0.735***
Missing/Imputed		0.123***	0.118***		0.082***	0.070***
Race/Ethnicity						
Hispanic	0.837***	0.836***	0.876***	0.891***	0.896***	0.929*
Black	2.298***	2.296***	2.403***	2.744***	2.810***	2.929***
Other	0.910***	0.910***	0.911***	0.834***	0.834***	0.825***
Not Reported	0.370***	0.370***	0.366***	0.423***	0.426***	0.425***
Gender						
Single Male	1.329***	1.329***	1.321***	1.372***	1.385***	1.383***
Single Female	0.949**	0.951**	0.972	1.032	1.034*	1.048**
Not Reported	1.063	1.056	0.980	1.108	1.068	0.991
Economic Conditions						
Mortgage Rates	0.725***	0.726***	0.777***	0.661***	0.663***	0.699***
Change in Mortgage Rates	1.183***	1.182***	1.092***	1.323***	1.312***	1.257***
Application Rate	0.993***	0.993***	0.996***	0.993***	0.994***	0.996***
Denial Rate	1.011***	1.011***	1.004*	1.018***	1.018***	1.007***
FHA Share	1.029***	1.029***	1.022***	1.032***	1.032***	1.031***
Unemployment Rate	1.052***	1.052***	1.068***	1.025***	1.025***	1.039***
Employment Change	1.022***	1.022***	1.020***	1.013***	1.013***	1.016***
Delinquency Rate	1.074***	1.074***	1.081***	1.065***	1.065***	1.075***
Housing Price Change			1.024***			1.012***
Average Sales Price (Log)			0.831***			0.958***
Observations	255,488	259,594	244,845	638,527	679,769	634,384
LR χ^2	55,747***	56,615***	54,740***	3,006,741***	3,565,905***	3,375,014***
AIC	294,888	295,757	268,807	36,257,952	37,637,084	34,633,244

AIC = Akaike information criterion. FHA = Federal Housing Administration. LR = likelihood ratio.
*Note: Statistically significant at the *** 0.001 ** 0.010 * 0.050 level.*
Source: Author tabulations of Federal Housing Administration administrative data

Exhibit 9

Odds of FHA Relative to Other Subordinate Lien Improvement Loans, 2018–20

	(1)	(2)	(3)	(4)	(5)
Income (Log)	0.859***	0.860***	0.905***	1.316***	1.292***
Missing/Imputed		0.210***	0.075***	0.214**	0.237*
Credit Score			0.995***	0.994***	0.994***
Property Value (Log)				0.481***	0.457***
Race/Ethnicity					
Hispanic	0.609***	0.612***	0.562***	0.340***	0.355***
Black	1.142*	1.143*	0.979	0.767*	0.718**
Other	0.808***	0.810**	0.758***	0.885	0.923
Not Reported	0.682***	0.681***	0.657***	0.960	1.010
Gender					
Single Male	1.434***	1.438***	1.391***	1.610***	1.622***
Single Female	0.978	0.982	0.954	1.250**	1.282**
Not Reported	0.484***	0.483***	0.453***	0.645*	0.591*
Economic Conditions					
Mortgage Rates	1.515***	1.505***	1.507***	3.468***	2.921***
Change in Mortgage Rates	0.774***	0.776***	0.757***	0.553***	0.623**
Application Rate	0.993***	0.993***	0.993***	1.000	1.003
Denial Rate	1.006	1.008*	1.004	1.001	0.990
FHA Share	1.016***	1.016***	1.014***	0.998	0.997
Unemployment Rate	0.958***	0.959***	0.964***	0.955*	0.965
Employment Change	0.967***	0.967***	0.967***	0.978	0.988
Delinquency Rate	1.385***	1.380***	1.416***	1.479***	1.522***
Housing Price Change					0.931***
Average Sales Price (Log)					0.995
Observations	749,565	764,729	700,648	694,043	661,276
LR χ^2	758,919***	773,144***	1,280,698***	1,316,274***	1,281,611***
AIC	10,852,522	11,082,504	9,856,900	9,732,379	9,248,785

AIC = Akaike information criterion. FHA = Federal Housing Administration. LR = likelihood ratio.
*Note: Statistically significant at the *** 0.001 ** 0.010 * 0.050 level.*
Source: Author tabulations of Federal Housing Administration administrative data

Higher-income borrowers are less generally likely to use FHA-insured loans relative to other subordinate lien home improvement loans. However, that relationship flips in the fourth column of exhibit 8 after accounting for property value, which is only available in HMDA after 2017. Borrowers with lower-valued properties are more likely to use FHA property improvement loans. Conditional on property value, however, lower-income borrowers are more likely to use cash out refinances and HELOCs and less likely to use FHA. On the other hand, borrowers without any reported income are much less likely to use FHA. The results must be interpreted with caution given that roughly two-thirds of FHA loans do not report property value, likely because a property appraisal is not required. Borrowers with lower credit scores (also only available in the second sample) are more likely to rely on FHA.

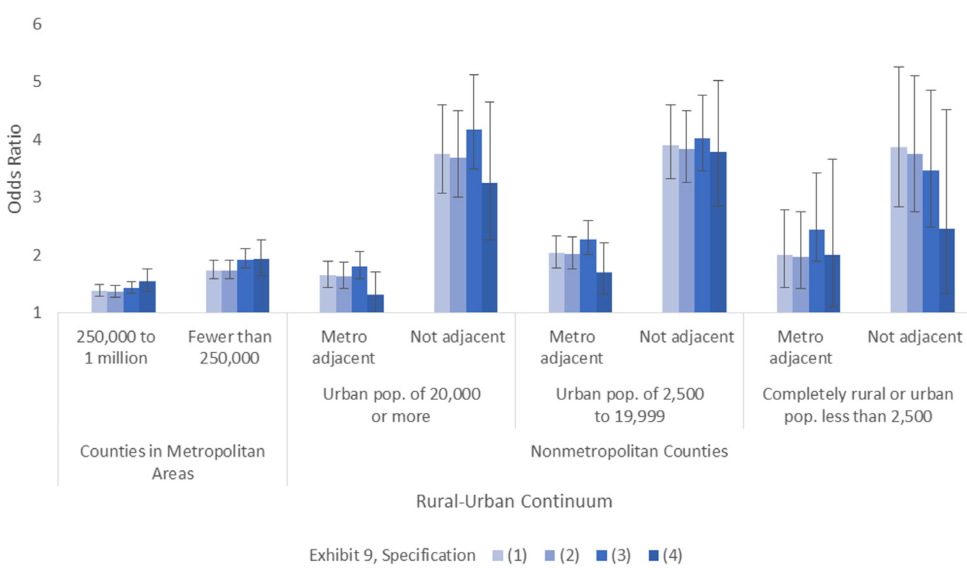
Minority borrowers are generally less likely to use FHA. Whereas the estimated coefficient associated with Black borrowers is initially positive, the sign flips in the third column of exhibit 9 after accounting for credit score. Controlling for credit score, Black and Hispanic borrowers are less likely to use FHA than any of the alternative possible options for property improvement. FHA is more likely than any alternative to be used by single applicants, particularly single males.

Several of the coefficients associated with economic conditions are not consistent across exhibits 8 and 9 or not statistically significant in the final specifications of exhibit 9, which may be because the second sample relies on a shorter study period with less variation in economic conditions. One consistent finding, however, is that FHA is more relied on than any alternative when and where mortgage delinquency rates are higher.

FHA also has a higher market share in rural counties. Exhibit 10 plots the odds ratios for the first four specifications in exhibit 9.[25] FHA has a larger market share, controlling for borrower characteristics and economic conditions, in smaller metropolitan areas and in counties outside any metropolitan area. In particular, the likelihood of using FHA-insured subordinate lien property improvement loans was roughly 4 times greater in counties not adjacent to a metropolitan area compared with counties in metropolitan areas of over 1 million people (the reference group). FHA accounts for only about 1-in-15 close-end subordinate lien property improvement loans in these counties, however, and only 1-in-500 loans including other financing options.

Exhibit 10

FHA Rural-Urban Odds Ratios



FHA = Federal Housing Administration.
Source: Author tabulations of Federal Housing Administration administrative data

[25] The fifth specification had a limited number of observations in several RUCC categories, leading to wide confidence intervals, but had otherwise similar point estimates.

Conclusion

FHA is primarily known for insuring home mortgages; however, assisting the financing of home repairs and improvements was a significant part of the agency's early history. The Title I property improvement program has declined over several decades due to difficulty monitoring contractors and the quality of their work, loan limits that have not increased since 1994, and antiquated underwriting and processing procedures, as well as the growth of conventional financing alternatives.

Nevertheless, Title I continues to serve particular segments of the home improvement finance market. Similar to its role in the mortgage market, FHA disproportionately serves borrowers with lower credit scores who might have difficulty obtaining conventional credit. In fact, Title I property improvement loans do not have a minimum credit score requirement. Title I also has a higher share in markets with higher delinquency rates when and where conventional credit is often less available, fulfilling FHA's countercyclical role.

Title I borrowers are also typically lower-income than conventional borrowers. Title I, however, is associated with higher incomes after controlling for property value. This may be due to underwriting standards still focused on ability to repay, whereas conventional options like cash-out refinancing and home equity lines of credit depend more on available home equity. This is also why few Title I borrowers are missing income in HMDA, but most borrowers do not report property value. FHA also offers cash-out refinances and home equity conversion mortgages (also known as “reverse” mortgages) to extract home equity that could be used for property improvements. With 203(k) rehabilitation mortgages, borrowers may finance projects based on the property value after improvements rather than the current, lower value. Title I is unique in offering property improvement loans without requiring an appraisal. This may be why Title I disproportionately serves rural housing markets, where property valuation is more difficult due to fewer sales and a more heterogenous housing stock.

The PowerSaver pilot demonstrates how Title I could be modernized to address energy efficiency and climate change. The residential sector accounts for roughly one-fifth of the total energy consumption (Energy Information Administration, 2022). New construction accounts for roughly only 1 percent of the housing stock each year; therefore, existing homes will need to be renovated to substantially reduce residential energy consumption. According to EnergySage, the installation of a solar panel system costs between $25,000 and $30,000 on average before incentives and rebates (EnergySage, 2021). Even basic retrofits, however, like insulation, new windows and doors, and more energy efficient heating and air conditioning systems can make a meaningful difference not only in a homeowner's carbon footprint but also their utility bills.

Title I also has the potential to help finance the construction of accessory dwelling units (ADUs) to ameliorate the nation's lack of affordable housing. World War II provides a precedent for how the program could be modified to address a housing shortage. The maximum loan limit on multifamily homes was doubled in 1941 to promote converting single-family homes into multifamily to accommodate the influx of defense workers (Harris, 2012). According to the National Association of Home Builders (Emrath, 2019), three-fourths of ADU projects cost at least $50,000, including 28 percent that cost $150,000 or more. The current loan limit formula, however, is only $25,000 for a single-family home or $12,000 per unit up to $60,000, which results in a lower limit for a two-unit property than a single-family property.

Regardless, Title I regulations follow Title II in classifying ADU tenants as boarders in a single-family home, requiring 2 years of rental payment history in order to be included in effective borrower income. For comparison, Title II regulations permit including rental income of two- to four-unit properties in effective income based on operating income, lease agreements, or fair market rent. The distinction between ADU and second unit is vague but has important consequences for access to credit.[26] Allowing homeowners to effectively borrow against future rental payments may allow them to finance the construction on ADUs and expand housing supply, even if they currently lack sufficient income and home equity to cover the costs of conversion. More research is needed on the performance of mortgages on homes with ADUs to understand whether and how rental income should be incorporated into underwriting standards.

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[26] FHA's Single-Family Handbook states, "As part of the highest and best use analysis, the Appraiser must make the determination to classify the Property as a Single Family dwelling with an ADU, or a two-family dwelling. The conclusion of the highest and best use analysis will then determine the classification of the Property and the analysis and reporting required … An ADU is usually subordinate in size, location and appearance to the primary Dwelling Unit and may or may not have separately metered utilities or separate means of ingress or egress" (FHA, 2022: 585).

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