

Examining the Transition to HUD Small Area Fair Market Rents Using Craigslist Data

Aksel Olsen

Association of Bay Area Governments and Metropolitan Transportation Commission

Abstract

The limitations of the U.S. Department of Housing and Urban Development's (HUD) metropolitan-scale, American Community Survey (ACS)-driven annual Fair Market Rent (FMR) estimates are familiar to local housing officials. Each year, scores of comment letters are received by HUD as FMRs are updated and implications for local housing markets become known. The transition to Small Area Fair Market Rent (SAFMRs) holds great promise in mitigating key shortcomings of using areawide geography, offering a much more submarket-specific variable payment standard for use by public housing authorities (PHAs). This potentially opens up more high-opportunity areas to the program's users. A more formal, large-scale assessment of this key rental housing policy, however, has been difficult due to paucity of current national yet sufficiently local, datasets describing rental housing markets. Using recent and spatially comprehensive rental data from Craigslist, a listing website that includes housing, we analyze HUD data for 2,600 FMR areas nationwide and show rental gaps between the actual cost of rentals and what PHAs will pay per the FMR payment standard. We analyze how a shift to SAFMRs changes the potential availability of units, focusing on both the 24 HUD rule areas and the nation at large. Based on our findings, we argue that more areas should be included in the program if appropriate safeguards can be instituted.

Introduction

In a report to Congress in 2017, the U.S. Department of Housing and Urban Development (HUD) quantified the scarcity of affordable rental housing, noting that, “[n]ationwide, only 66 affordable units exist for every 100 extremely low-income renters” (Watson et al., 2017). The situation is not improving. Renters have faced a faster increase in rents relative to incomes, with 4 out of 10 renters paying rents that used to be in the top quartile in 2000. In coastal markets, affordability challenges are even more pronounced, with affordability having deteriorated considerably since 2000 (Myers and Park, 2019). While it is true that many markets could be substantially helped by an increase

in the supply of affordable housing, how the existing stock is managed and available to different income groups, including through federal programs such as the HUD's Housing Choice Voucher (HCV) program, remains critical to low-income families throughout the country.

HUD has long provided a lifeline to millions of low-income renter households, subsidizing their housing each year. While the department has a range of programs supporting the poorest Americans, the largest by far in terms of outlays, is the HCV program (McClure, Schwartz, and Taghavi, 2015). The HCV program, administered by HUD, supports over 2.2 million households, or about 4.5 percent of all rental households, each receiving rental subsidies ensuring that their rent does not exceed 30 percent of their income. Forty percent of HCV holders are female-headed households with children (HUD, 2019). The program has undergone changes in funding and scope since its inception in the Housing and Community Development Act of 1974, yet it remains a key pillar of today's tenant-focused (as opposed to project-focused) federal housing policy.

One of the determinants for access to users of the voucher program is a key regulatory feature of the program's implementation: the scales and geographies of Fair Market Rents (FMRs), which are the HUD-provided metropolitan-scale maps denoting what a unit would rent for in a fair market transaction in a given FMR area. By definition, FMRs are set at the 40th percentile of rents for units of different bedroom counts, meaning about 4 out of 10 units should be nominally available to voucher holders. Two challenges have long been associated with the program. First, there is the issue of whether sufficient numbers of units are available to voucher holders in different markets. If a much smaller sliver than the 40th percentile would be available, it would create more competition and limit options for program participants (as well as to low-income households in general). Second, and relatedly, a limited stock typically translates to a limited geography, with households more prone to concentration in high-poverty, high-segregation neighborhoods.

Both factors—scarcity and concentration in high-poverty areas—have been demonstrated empirically over the years by HUD and others. As a way to address both, HUD recently transitioned a small number of areas to Small Area Fair Market Rents (SAFMRs), a much finer-grained estimate of rents. SAFMRs allow subsidies to be higher in more expensive areas, while conversely reducing them in more affordable ones. This could open access to new markets for many low-income Americans. The Final Rule on establishing SAFMRs was issued in the second half of 2016, requiring implementation for 24 HUD-defined metropolitan areas. HUD has issued interim and final reports on six pilot study areas, with early implementation of the shift from FMRs to SAFMRs. While interim and final evaluation reports suggest promising outcomes in terms of offering more units in higher opportunity neighborhoods, assessments including larger geographies have yet to be done.

This study relies on a recent national sample of rental data scraped from Craigslist, a listing website, to provide early insights into HUD's transition to SAFMRs. The rental listings are geocoded and can thus be classified by both the old "large area" FMRs as well as by the new SAFMRs, allowing us to identify transitions—listings that were too expensive in the old classification but fall below SAFMRs per the new schema. Although in many high-cost markets, the existing FMR system means many neighborhoods are de facto rental deserts, with few rental listings available below applicable FMRs, we find the situation to be much improved with SAFMRs. We discuss limitations with the analysis as well as offer suggestions for the program.

We start the article with a review on the background of the FMR program, highlighting key challenges, from concentration to measurement issues. We motivate the study in the context of data limitations and the value in triangulating with an independent source. We then describe the data and report on findings for the United States as a whole and for the 24 mandatory areas under the SAFMR final rule (Rule Areas). We suggest other areas that could be added and then discuss our findings.

Background: HUD's Housing Choice Voucher Program in Brief

The HCV program, also known as the Section 8 program, helps households afford housing in the private market by topping off the rent they are able to pay (set at 30 percent of their income), up to the going market rate for a standard quality unit.

The program hinges on annually published FMRs for each of about 2,600 metropolitan and non-metropolitan areas nationwide, determining the typical cost of a non-luxury unit. Local public housing authorities (PHAs), in turn, use FMRs to set the payment standard for how much a unit should rent for and, accordingly, what the size of the subsidy should be for individual voucher holders at lease-up. The tenant pays 30 percent of their income, and the program pays the difference up to the lesser of the gross rent for the unit or the payment standard amount set by the PHA.

The voucher program is not an *entitlement* where every eligible family receives a voucher but a benefit subject to waiting lists for vouchers to become available. Implementation details of the program, such as how FMRs are determined, have a big bearing on how many households can be supported and where those households will end up living *within* regions. As an example, potential voucher tenants accessing the Berkeley Housing Authority's website during the spring of 2019 would find the waiting list closed; it was last open for 5 days during the summer of 2010 and some 37,000 people applied for a spot there (Berkeley Housing Authority, 2019). Nationally, an eligible family that has secured a spot on the waiting list will wait an average of 2.5 years for a voucher (Watson et al., 2017). Some markets see much longer waiting times; for example, in 2017, Santa Cruz reported a waiting period of 8 years (Panetta, 2017). An unfortunate lack of centralized data on waiting lists compiled from individual PHAs precludes systematic analysis of the predictors of waiting list length. For many, the program is all but off-limits and not a predictably reliable plank on which to build a family's housing career.

In addition to being consequential for individuals, implementation details matter to the overall fiscal health of the local PHAs managing the programs for HUD. If FMRs are set too low, underestimating the "true" cost of rentals, many households won't be able to secure a lease as they cannot compete with non-subsidized renters; that would negatively affect the program's "success rate," which hovers in the mid-30s in percentage terms in a large national assessment (Finkel and Buron, 2001). To the extent that the payment standard is set too low in some FMR areas with scarce affordable housing stock, those markets may, from the vantage point of low-income renters and voucher holders, effectively function as rental deserts. In rental deserts, expansive and expensive housing searches are conducted, with considerable difficulties securing leases, particularly in neighborhoods offering opportunities. This scarcity is exacerbated by low turnover,

loss of landlords to the HCV program, as well as gentrification of typically amenity-rich, centrally located areas historically affordable to low-income individuals (Hwang and Lin, 2016; Somerville and Holmes, 2001).

Conversely, if rents are set too high with higher FMR levels, landlords may absorb the higher rents payable rather than provide more housing service, getting more money from the federal government in the process (Collinson and Ganong, 2018). This would deplete funds and could ultimately make fewer vouchers available for families in that area. Many local PHAs from high-cost areas watch, not surprisingly, with great interest as rents are published ahead of each fiscal year (FY), writing comment letters challenging local FMR determinations, using pointed language such as “unfathomable” to describe the published rents (Fredericks and Havlicek, 2017).

Well-Known Voucher Program Challenges

Metro-Level Rents Ignore Submarkets

High-cost areas with rapid rent increases will, all other things equal, have a harder time getting FMRs to catch up with local markets, but geography matters, too. The larger the region, the more internal variation of rental rates from one neighborhood to the next. This variation is attributable to a range of factors related to accessibility to jobs, open space, and other amenities, as has long been well documented by the hedonic housing price literature (Bayer et al., 2016; Knaap, 1998; Rosen, 1974). FMR areas as regions in their own right, typically have a number of relatively distinct housing submarkets, each with their own characteristics and cost structures (Bourassa et al., 1999). While PHAs can set payment standards from 90 to 110 percent of FMRs, many FMR areas exhibit a much larger variation in rental costs between submarkets. Having uniform FMRs for such areas means that the voucher subsidy will be the same in the most expensive areas as in the most affordable parts of the FMR area. This effectively limits the geography of *where* the vouchers will likely be used, increasing the likelihood that lease-ups will be in the least desirable parts of the region. This is in contrast with program objectives of poverty deconcentration, while certainly flying in the face of the key premise of the program: that households be given a meaningful choice of housing options.

Deconcentration

Deconcentration has long been recognized as an important objective of the affordable housing programs,¹ due to poor outcomes on a range of development indicators from growing up in high-poverty, segregated neighborhoods. While there was little doubt that living in concentrated poverty was not beneficial, the record on dispersal programs had long been less than convincing (Goetz and Chapple, 2010). HUD’s own Moving to Opportunity (MTO) for Fair Housing demonstration program has provided important experimental data underlying the policy importance of neighborhood quality, even if the mechanisms may not be fully understood. Leveraging these longitudinal data, Chetty and collaborators (2015), in a set of groundbreaking studies, have provided new insights from the MTO program data linked to administrative records. They convincingly demonstrated the long-term, positive effects of moving away from poverty-

¹ “Fair Housing Act of 1968.” 1968. 42 U.S.C. 3601.

stricken neighborhoods before children reach adolescence, profoundly influencing individual life trajectories (Chetty, Hendren, and Katz, 2015). Whether the key policy implication of MTO is to address the root causes of poverty, fix the social fabric of existing neighborhoods, or encourage moving residents, concentration in high-poverty neighborhoods remains a reality for many voucher holders.

More than 20 years ago, Newman and Schnare (1997) found that, by giving tenants choices not present with a policy based on place-bound, project-based assistance, the voucher programs appeared to do little to help improve neighborhood quality of residents, although the voucher program appeared to “reduce the probability that families will live in the most economically and socially distressed areas.” Almost twenty years later, McClure and Johnson (2015) revisited Newman and Schnare’s work, noting some success in terms of moving more households into low-poverty, less distressed areas—including suburbs—though still finding much room for improvement on racial integration and other factors.

A considerable amount of research, including research from HUD, has documented this very challenge of deconcentration of voucher holders away from the most impoverished neighborhoods. A number of studies have assessed particular markets with respect to the deconcentration goals motivating the program (De Souza Briggs, Comey, and Weismann, 2010; Lens, Ellen, and O’Regan, 2011; McClure, 2008; McClure, Schwartz, and Taghavi, 2015; Varady et al., 2010). Section 8 households are concentrated in relatively high-poverty neighborhoods (Wang and Varady, 2005). McClure and colleagues (2015) found that one in five voucher households situate in low-poverty neighborhoods, although voucher holders were a small share of the housing stock and are not particularly spatially concentrated. Pendall (2000) documented an association between high rates of poverty and the concentration of voucher holders in neighborhoods of distress. Higher vacancy rates, however, were found to increase the ability of households to move to areas of higher opportunity (Galvez, 2010), a finding consistent with the concerns raised by commenters on HUD’s Proposed Rule on SAFMRs: That the program would be less successful at providing deconcentrating in markets with very low vacancy rates (HUD, 2016c).

Why are Voucher Holders Persistently Concentrated?

Lack of deconcentration is thought to be due in no small part to the payment standard being too low for program design reasons. With the payment standard uniformly set for a metropolitan area, higher cost areas will automatically be off-limits. Recent supporting evidence comes from Wang’s analysis of survey data from Florida, which show a marked difference between voucher holder stated preferences for safe and clean neighborhoods with good schools and the neighborhoods they could *actually* afford (Wang, 2018).

The assumption is that concentration has persisted for financial reasons, with payment standards set such that good neighborhoods were off-limits, although other plausible reasons have been identified.

Landlords may not actually lease to voucher holders, as was recently reported by both the *Los Angeles Times* and Pew Research (Khoury, 2019; Wiltz, 2018). In a landmark study of landlord behavior, particularly whether would-be voucher holders would be treated differently than other

prospective tenants, researchers found the housing search process fraught with denials of voucher holders in more than 75 percent of cases in some markets (Cunningham et al., 2018). This is a longer standing challenge, having accompanied the program perhaps since its inception (Tighe, Hatch, and Mead, 2017). Building trust and long-term relationships with landlords is accordingly critical to overall program success (Varady, Jaroscak, and Kleinhans, 2017). Many landlords are anecdotally leaving the program, however, representing an erosion of long-term relationships with PHAs.²

The program may fail to further deconcentration objectives for a number of reasons not necessarily directly related to the program itself, such as lack of social networks in higher opportunity neighborhoods or limited transportation options (McClure, 2008; Ruel et al., 2013).

Further, beyond payment standards, counseling appears to be an important factor for families to successfully secure housing in low-poverty neighborhoods (Turner and De Souza Briggs, 2008). Voucher holders generally have 60 days to search, select, and secure a lease after voucher assignment. Whether it is search difficulties, preferences, or discrimination, it follows that not all searches will be successfully turned into a lease, even if the listing price is technically within reach, or leases may not lead to the most promising neighborhoods given the typically higher cost they command (Shroder, 2002). In 2001, in a nationally comprehensive study, researchers found that the “success rate,” or the rate of success of securing a lease for voucher families, was just 37 percent (Finkel and Buron, 2001).

A more structural reason for lack of deconcentration success is that demand-side programs such as vouchers are unable to address a key underlying reason for high housing costs in many areas, such as limited supply and low vacancies. In particular, as many high-cost markets are supply constrained, vouchers are of less use in those areas.

HUD, however, has long focused on addressing this programmatic challenge. Already in 2000, the agency issued an interim rule stipulating both that (1) some areas could base FMRs on 50th percentile levels, departing from the typical 40th percentile standard, and (2) that PHAs would have more flexibility in diverging from the areawide rent ceiling, allowing them to set the voucher “payment standard” to between 90 and 110 percent of the published FMR for each unit size (HUD, 2000). This devolution of authority to the local level could mean PHAs could be much more responsive to local conditions and knowledge. Ultimately though, HUD assessed that the 50th percentile approach failed to sufficiently reduce the concentration of voucher holders in high-poverty areas.

Toward Small Area Fair Market Rents

As the 50th percentile approach failed to sufficiently deconcentrate voucher holders, the most recent evolution involves adjustments to the geography of the FMRs. In tandem with yearly small-area data from the American Community Survey (ACS) that started to be available in 2011, HUD issued a notice that it would begin a pilot demonstration project for a small number of PHAs to

² Contra Costa County, for example, reported a drop of 631 landlords in recent years as they could lease to non-HCV renters (Villareal, 2016).

use a new methodology of ZIP Code-based FMR areas, called SAFMRs (HUD, 2010).³ By shifting to ZIP Codes instead of metropolitan statistical areas (MSAs), rents would be able to track submarkets better, instead of treating housing markets as wholly uniform within an MSA-wide FMR area (HUD, 2016a). The premise of geographically rescaling FMRs to the much smaller ZIP Code tabulation area geographies is to allow voucher payments to track actual rents much closer than the one-size-fits-all per the FMRs, meaning a much more variable payment standard within each FMR area. With the more nimble SAFMRs, households would therefore, in principle, be better able to locate in relatively higher opportunity areas, which typically are more expensive, than what they would have been able to with existing policy under prevailing FMRs. At the same time, the SAFMRs would also “prevent undue subsidy in lower-rent areas (HUD, 2010). Where the 2000 Interim Rule also increased the FMR ceiling for MSAs to the 50th percentile rent, the difference is the finer geographic scale. An areawide increase in allowable rents did little to combat the locating of voucher holders in areas of concentrated poverty and economic and racial segregation, while likely subsidizing landlords offering substandard units. In practical terms, whereas there are around 625 unique metropolitan area-based FMRs, the number of SAFMRs is almost 25,000, a forty-fold increase in geographic resolution, which is substantially better able to track real estate submarkets than the metro-wide delineations they may replace.

To test the effect of migrating to smaller-scale FMR areas as a way to better enable voucher holders to reside near jobs, transportation, and educational opportunities, five PHAs with different demographic and economic characteristics agreed to participate in the SAFMR demonstration in 2012 (Finkel et al., 2017). The demonstration project would test key outcomes for a handful of PHAs before rolling out the program as a replacement to the 50th percentile FMR areas.

Expectations and Early Assessments

By 2017, an Interim Report on the pilot areas was issued, demonstrating that this was indeed the case; that by re-carving metropolitan area geographies into ZIP Code-level specificity, the distribution of rental units tended to shift to relatively more expensive areas, often doubling as areas of higher opportunity (Finkel et al., 2017). The study also noted, however, an overall decline in units affordable to voucher holders in those areas.⁴ Still, based on those findings, HUD issued a final rule that SAFMRs would become active in the 24 Rule Areas, generally higher cost FMR areas, or areas with a high concentration of voucher holders in poverty (HUD, 2016c). After pushback from stakeholders and some PHAs, HUD announced a delay in the implementation of SAFMRs for the 24 Rule Areas to FY 2020, citing the desire to complete the full pilot study and more fully analyze potential downsides of the transition (HUD, 2017b). A legal challenge was filed by two voucher holders and a nonprofit organization devoted to providing housing opportunities for low-income people in Connecticut, with the District of Columbia Circuit

³ The SAFMR demonstration consisted of five PHAs: The Housing Authority of the County of Cook (Illinois), the City of Long Beach (California) Housing Authority, the Chattanooga (Tennessee) Housing Authority, the Town of Mamaroneck (New York) Housing Authority, and the Housing Authority of Laredo (Texas). In addition, the evaluation of the demonstration study included two PHAs from the Dallas, Texas metropolitan area, the Housing Authority of the City of Dallas and the Housing Authority of Plano, which have both been using SAFMRs since 2011 as the result of a legal settlement.

⁴ The opportunity index constructed for this study includes percent nonpoor, school proficiency, job proximity, and environmental quality.

Court enjoining HUD to continue with the SAFMR as HUD had not made the proper procedural findings necessary for a delay.⁵

As SAFMRs were officially rolled out in 2018, an early assessment came from the New York University (NYU) Furman Center. They expanded HUD's Interim Report analysis of the pilot SAFMRs demonstration to the 24 FMR areas mandated to use SAFMRs under the 2016 SAFMR Final Rule (NYU Furman Center, 2018). They analyzed the introduction of SAFMRs in these 24 Rule Areas, using ACS data tabulated for HUD on rental units and their rent distribution at the Zip Code Tabulation Area (ZCTA) level, and found that switching to SAFMRs *furthered* housing options in higher-rent ZIP Codes while *reducing* them in lower-rent ZIP Codes, which was consistent with program purposes. Somewhat in contrast with the pilot, their analysis also found that, in total, the number of units affordable to voucher tenants would increase with the use of SAFMRs when looking at the 24 Rule Areas as a whole (NYU Furman Center, 2018).

Palm (2018), in an assessment of the program using non-census rental data from Rent Jungle, a web listing aggregator, analyzed rents from two time periods in five FMR areas and similarly found that the switch to SAFMRs would positively influence availability of units in higher opportunity neighborhoods; that finding stresses the importance of the geographic scale of the program. He further found different trajectories in different areas. Sacramento, for example, would benefit from inclusion in the SAFMR program as the switch would mean a substantial increase in listings affordable in low-poverty neighborhoods, without an offsetting “cataclysmic loss” of listings in higher poverty areas. Overall, the assessments of the switch so far are encouraging, though issues of measurement will remain a challenge.

Key Measurement Challenges and Motivation

A difficulty in assessing FMRs comes from the data used to calculate FMRs in the first place; ACS data. While nationally comprehensive, the data are collected by an ongoing survey throughout the year with 1-year data released for larger geographies (areas representing more than 65,000 persons). For all its wonders as a timely, repeated, and comprehensive data resource for researchers, a sample-based survey such as ACS presents unique analytical and programmatic challenges when using it for program development and, in particular driving regulatory geographies of FMRs. HUD, in 2018, indeed noted that “[i]n general, it is difficult to measure the accuracy of FMRs for the simple reason that no single, widely accepted measure of gross rents exists to use as a benchmark to compare with the FMRs” (HUD, 2018). While it is instructive to assess unit availability below FMRs using the special tabulations of the inventory of rental units by rent at the level of ZCTAs provided by HUD, by definition, availability largely follows FMRs quite closely as program and evaluation is defined using the same source. Many PHAs, in their comments on annual releases of FMRs, indeed note the challenges related to using ACS data, the lags it necessarily entails, and the challenge of tracking fast-moving markets with higher than average increases in prices not captured by the current usage of national trend factors.

“In 2013 and 2015 the eight PHAs in the [Oakland-Hayward-Berkeley, CA] Metro Division paid for and conducted a statistically valid rental survey in order to refute proposed FMRs

⁵ *Open Communities Alliance Et Al v. Carson Et Al*, Civil Action No. 17-2192 (BAH). 2017. Washington, D.C.

that either were drastically low given our rental market or reduced from the previous year. In both 2013 and 2015, the FMRs were significantly increased as a result of the study data (approximately 16 percent in 2013 and approximately 34 percent in 2015), thus demonstrating the inadequacy of HUD's FMR methodology" (Villareal, 2016).

While SAFMRs represent a clear conceptual and policy-wise great leap forward recognizing the significant intra-regional housing market heterogeneity, questions of measurement will nonetheless continue to be an issue. The core challenge, only made more acute when going to the smaller ZCTA level, is intrinsically related to capturing at relatively fine spatiotemporal detail the behavior of the rental housing market with a survey with a *locally* modest sample size, coupled with the requirement for both spatially and temporally detailed data on rents for different unit sizes. The need for timely data requires further subsetting to recent movers to capture recent inflation, further limiting the sample. HUD's guidelines are such that estimates with a margin of error ratio larger than 50 percent are not to be used for calculating base rents and recent move factors. This means a wide band around a point estimate would be acceptable, and necessary (HUD, 2015). HUD caps possible year-over-year decreases to 10 percent, effectively smoothing the effect of such measurement volatility (HUD, 2017a).

Apart from sampling error, there is the challenge of using a survey that is not ideally suited as a housing survey. Some commenters on annual FMR notices in the Federal Register have noted, in connection with the requirement that HUD exclude subsidized households from the ACS rental data, the difficulty of properly identifying and discarding them. HUD, however, handles that by truncating the bottom of the rental distribution using administrative data on assisted housing rents before calculating the 40th percentile. Similarly, some major cities, typically in expensive coastal markets, have rent control, which could serve to downward bias FMRs in exactly the costliest markets. In sum, inasmuch as these factors affect FMR levels, having external data to compare against FMR levels is critical, highlighting the value of separating training and validation data for FMRs.

Such assessments with ACS-independent data are rare, however, mainly because few nationally comprehensive datasets exist on rental markets. While there is a strong data infrastructure associated with home sales in the form of recorded transactions, rents leave far fewer traces to track them effectively and across geographies. It is typical for vendors to exist in particular markets. While the localized nature of rental information makes generalized, consistently measured assessments difficult, it by the same token makes it hard to do larger scale accounting of the housing program. Assessments have accordingly typically focused on individual areas due to data limitations. Holding some promise, but nonetheless representing the problem of aggregation, as well as of fair use, the increase in the number of web platforms has given rise to big data collection efforts; that potentially offers insights into a range of domains, including rental markets, if the data are available to harvest and prove to be reliable.

A few researchers have relied on such big datasets to answer questions related to housing markets and FMRs, offering a triangulation independent of ACS data. Boeing and Waddell (2017) used Craigslist to assess FMRs nationally in a demonstration project of using big data to address substantive social science research questions, while at the same time comparing the rental data to

federal sources. While they found 37 percent of listings to be below FMR levels, close to the 40th percentile defining the program, they found many variations between metropolitan areas, with costlier FMR areas falling in the single digits. More recently, Palm (2018) provided preliminary evidence that suggested the transition to SAFMRs would overall lead to more units in higher opportunity areas. While Boeing and Waddell analyzed listings relative to FMRs, this study extends the work by reporting on the transition from FMRs to SAFMRs. This article expands the conversation and provides more detail on the potential for the program to move households into higher opportunity neighborhoods with the transition to a more fine-grained regulatory geography.

The Current Study

What will Small Area Fair Market Rents mean for would-be voucher holders across the 24 Rule Areas? This study explores differences in rental listing availability using a national dataset following the introduction of SAFMRs in the 24 Rule Areas. While there are only 24 areas that were mandated to use SAFMRs under the final rule, we expand the comparative analysis to include all areas for which SAFMRs are published, to cast a wider net on the effect of this type of geographical-regulatory reclassification, including to assess which non-rule areas would be well suited for using SAFMRs.

To gauge the availability of units at the relevant price point, this study relies on data scraped from Craigslist, a rental listings site, to characterize the voucher program. Using alternate sources of data to illuminate large scale urban phenomena is part of a wider emergence of “urban analytics” (Goodspeed, 2017). These alternatives rely on an array—often implied to be “bigger” and more “real time”—of sources of data and are often of a volunteered nature from “citizen sensors,” with questions as to both motivation and accuracy (Goodchild, 2007). In the case of data from Craigslist, listings are provided for business reasons by owners of units or companies managing units on an owner’s behalf.

Description of Dataset

The national sample⁶ covers the first 6.5 months of the federal FY 2019, beginning October 1, 2018. We note that using data covering the first half of the FY, should all other things be equal, leads to a better match with the FMRs, as it will cover the period least affected by inflation over the course of the year.⁷

While there are issues of accuracy and duplication, perhaps the most salient issue is that of coverage, since not all listings end up on Craigslist. As a non-research volunteered geographic information dataset, there is no standard for inclusion, no published benchmarks of market saturation and share, and coverage will vary over time and region, with usefulness needing to be determined on a case-by-case basis. Using data from a non-scientific sample, or in our case a form of “volunteered geographic information” (VGI) data, raises additional challenges, as the extensive

⁶ The listing data is scraped from Craigslist by UC Berkeley researchers using the Python-based Scrapy library. See Boeing and Waddell (2017) for details.

⁷ The listing data have not been adjusted for inflation or seasonality, nor would it be appropriate to do so: the rents such as they are, over the course of a year, will be what is compared with the payment standard over the course of the year.

quality control measures associated with the federal statistical infrastructure are entirely absent; the data generating process is not a neatly curated, purpose-driven sample, but rather one from data “in the wild.” The data are an artifact from the rental listing process; digital ephemera not meant to leave a footprint; and are in many ways the equivalent of looking at historical yellow page listings. To clean these, we went through a process similar to that described in Boeing and Waddell (2017), dropping formal duplicates (landlords reposting the same listing days later to generate more views). We similarly limited records to ones with valid geocoding. We filtered outliers using percentiles as well, but instead of defining outliers relative to the national distribution, we calculated outliers separately for each county to more closely reflect the norm for local markets.

To assess the dataset, we compared listings in our sample with the latest 1-year ACS release for 2017 at the core-based statistical area (CBSA) level for two pieces of information:

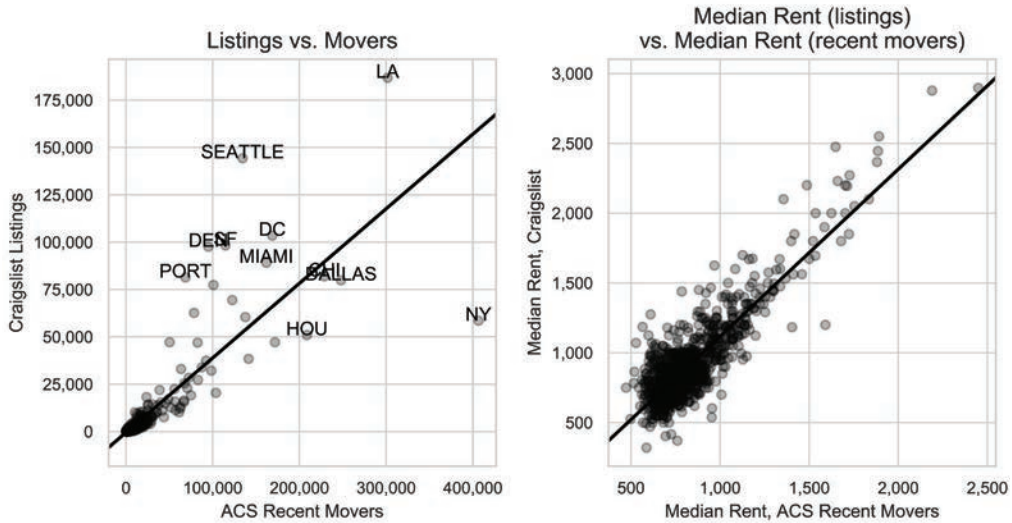
- Do the data roughly correspond to counts of recent mover households?
- Do the listing rents approximate those reported by ACS?

Listings and moves are distinctive conceptual worlds: Some people move more than once per year, but this is not captured by the ACS survey, asking “Where did this person live 1 year ago?” By the same token, the same unit may be listed more than once and appear more than once in the sample legitimately without being a duplicate. We would accordingly expect a larger number of listings than movers *if* the rental data represented the entire universe of listings, which of course they do not. Another difference is that listings may be akin to asking prices, and a lease may ultimately be signed with a rent below the advertised price, depending on the conditions of local markets.

In the aggregate, we found sufficient alignment in the two datasets to suggest reasonable accuracy. We found, first, a strong correlation ($R^2: 0.84$) between Craigslist listings and recent movers per ACS, and second, a strong correlation ($R^2: 0.86$) between median rents, both measured at the CBSA level. While these correlations were both strong, there were outliers particularly in the relationship between listings and moves. We mark a number of those on exhibit 1 and note that New York falls substantially below the regression line, having far fewer listings than the norm. New York’s rental market is heavily dominated by brokers, with accordingly a lower utilization of services such as Craigslist (Boeing and Waddell, 2017). On the other hand, the Los Angeles area has more listings than expected, as do MSAs around Seattle; Washington, DC; Denver; San Francisco; and Portland, to name the larger ones. Those housing markets could either see above average relocation activity, or those areas could be more prone to duplicates not caught by the heuristic approach sketched in exhibit 1.

Exhibit 1

Comparing Craigslist, ACS on Listings and Median Rent, CBSA Level



ACS = American Community Survey. CBSA = Core-Based Statistical Area.
Notes: Recent mover households comes from ACS table ACS_17_5YR_B25026, with the assumption that the share of recent mover renter households is the same as the share of recent mover renter population. The median rent ACS estimate covers renters who moved since 2015, per table B25113_002E.

Geographical duplication was widespread in the dataset. The scraped data comes with the listing ID assigned internally for tracking purposes by Craigslist. This ID will appear repeatedly if users resubmit the same listing days or weeks later to appear as a more current listing. These formal duplicates are removed. A more subtle class of duplicates involves new listings beyond resubmitting an earlier listing. In this case, in substance, the same unit is offered through several listings each with different IDs making them appear distinct. Depending on the market, this may take place over the course of several months as landlords may wait for a tenant to take the offered price, even on occasion lowering the rent to entice. We filter these by assuming that units on the same location (latitude/longitude) that have the same size in square feet, the same bedroom count and roughly the same price (within \$100 intervals) within a quarter is a duplicate. There will be boundary effects: Should the same listing be offered at the last day of the quarter and then a week later, they will be treated as distinct and kept in the dataset, whereas if both listings had been in the same quarter, they would have been flagged as duplicates.

This may falsely identify some listings as duplicates when they are in fact distinct units in larger multifamily buildings, though as the relisting practice appeared to be pervasive, this de-duplication approach was preferable to leaving them in the dataset. Absent a way to uniquely identify units in a building at the national scale, any practical use of such data will have to weigh the trade-offs of discarding too many or too few listings for filtering of the data for the purpose at hand. All said, as seen in exhibit 2, the sample went from 9.3 million to 2.8 million following de-duping and filtering procedures. A number of descriptive statistics are provided in the data appendix.

Exhibit 2**Key Descriptives for Dataset Before and After Filtering**

Subset	Area	Listings (Count)	Square Feet			Rent		
			Median	Mean	Standard Deviation	Median	Mean	Standard Deviation
Unique	U.S.	9,392,930	900	1,084	27,169	1,324	10,040	4,545,939
Geo Deduped	U.S.	2,845,445	967	1,331	41,665	1,400	25,276	7,843,509
Outlier Filtered	U.S.	2,816,757	967	1,063	523	1,405	1,646	1,003

Notes: Unique data contains one listing per listing ID. Geo Deduped data removes likely geographical duplicates of the same listing. The Outlier Filtered data excludes outliers measured on a rent per square foot basis.

Data on Opportunity Areas

Researchers have long called for better accounting of what constitutes quality in a neighborhood. As bigger datasets have become available, researchers are better able to come up with measures of neighborhood quality that go beyond the most typical proxies for neighborhood quality such as poverty (Pendall, 2000). To classify listings, we largely follow the approach set out in the HUD interim report, creating a composite index based on census-tract level components obtained from HUD's open data site (Finkel et al., 2017). Opportunity is understood as a resource or amenity available to residents in a given neighborhood.⁸ The components of the opportunity index include:

- A school proficiency index⁹ measuring neighborhood performance of fourth-grade students on state exams,
- An environmental health hazard index,¹⁰ measuring potential exposure to harmful toxins at a neighborhood level, including carcinogenic, respiratory, and neurological hazards,
- A jobs proximity index,¹¹ a gravity-based measure of jobs access within a CBSA,
- A low poverty index,¹² measuring share below the federal poverty limit.

Each is normalized on a scale from 0–100, with 100 considered higher opportunity. All indices are defined at the tract level. We average the components at the tract level to produce the composite opportunity index and then normalize it to a percentile ranking within each FMR area. A tract is accordingly classified in relative terms within the opportunity distribution of each FMR region with the implication that two tracts in different regions can have the same opportunity score though different underlying components. As we are interested in the relative opportunity for voucher

⁸ These are not to be confused with “opportunity zones,” which denote areas offering tax preferential treatment to investors. See <https://www.irs.gov/newsroom/opportunity-zones-frequently-asked-questions>.

⁹ <http://hudgis-hud.opendata.arcgis.com/datasets/school-proficiency-index>.

¹⁰ http://hudgis-hud.opendata.arcgis.com/datasets/c7e2c62560bd4a999f0e0b2f4cce2494_0.

¹¹ http://hudgis-hud.opendata.arcgis.com/datasets/4e2ef54b88084fb5a2554281b2d89a8b_0.

¹² http://hudgis-hud.opendata.arcgis.com/datasets/3419cb4c7aa144b2bc54671f58b580f4_0.

holders searching for housing within a region, the normalization is appropriate, and we report on listings availability by four opportunity categories.

Findings

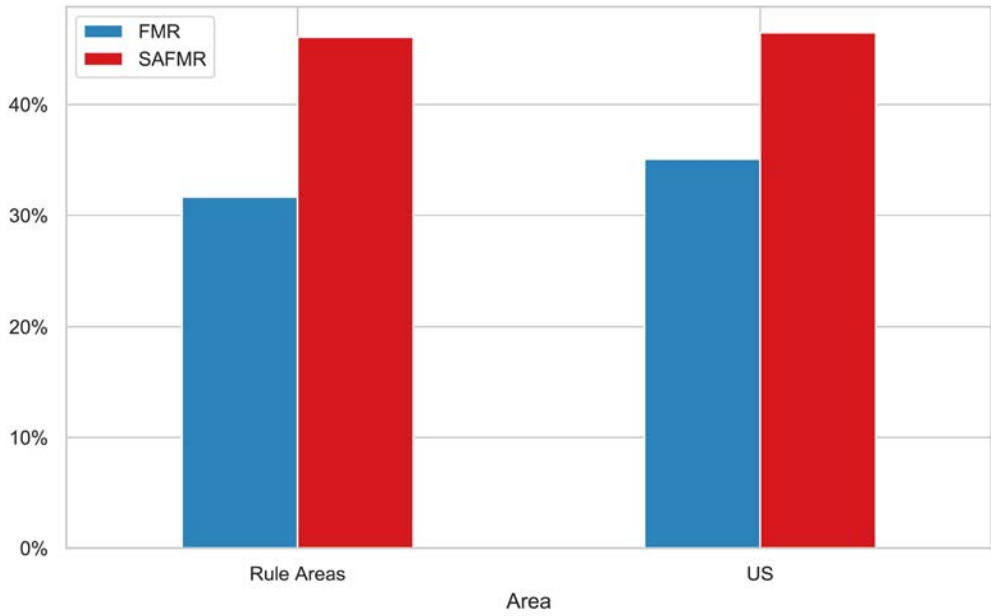
In the following sections when comparing the two, we refer to area-wide Fair Market Rent areas as MAFMRs, and the ZCTA-based FMRs as SAFMRs to avoid confusion. All other things equal, the expected number of listings below the FMR should represent 40 percent of the rental distribution as that threshold is used in their definition.

General Effect of Transition

Did the introduction to SAFMRs increase unit availability, overall, from MAFMR levels? Per exhibit 3, taken as a whole, nationally, we found that the share of listings was 5 percentage points below 40, at 35 percent, slightly smaller than the finding of 37 percent by Boeing and Waddell (2017).¹³

While the national count is reasonably close to the target 40 percent, many individual FMR areas see well below 40 percent of units available below the FMR level. For the 24 Rule Areas, the share is just 32 percent versus 35 percent for the United States as a whole. That availability is poorer in the 24 Rule Areas is not surprising given the selection criteria's focus on housing stock in relatively high-cost areas (HUD, 2016b). Consistent with program expectations, per exhibit 3, we note that the SAFMR transition, in the aggregate, moves availability up to the mid-40s, in percentage terms, for both the 24 Rule Areas and the larger list of 625 metro-based SAFMR regions, with more of an average increase for the 24 Rule Areas: Here, SAFMR would translate to an increase in available units by 14 percentage points given their lower starting point, consistent with the Rule Areas' selection criteria based in part on the low availability of units. Exhibit 3 further suggests benefits for a wider universe of areas than those identified in the Final Rule if the disruptive effects could be mitigated.

¹³ For FY 2019, only three areas relied on the 50th percentile FMRs, with many of the others having transitioned to SAFMRs. In the assessment of rents relative to FMRs, we use the 40th percentile FMRs for the areas currently using SAFMRs, which will mean poorer performance in those areas.

Exhibit 3**Overall Change in Listings Below Fair Market Rent Levels, by Area Category**

FMR = Fair Market Rent. SAFMR = Small Area Fair Market Rent.
Sources: Rental listings from Craigslist; FMR/SAFMR data from HUD

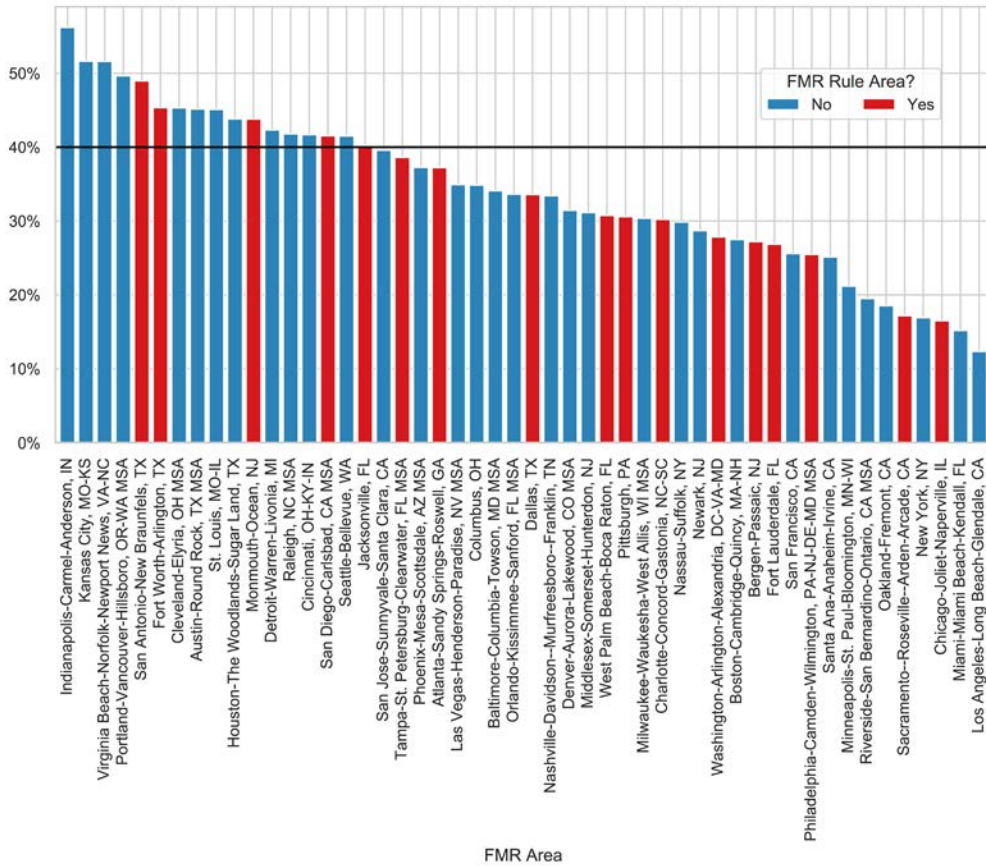
In some metropolitan areas, particularly in California, the share of units offered below FMR levels was markedly lower, with Sacramento and Los Angeles having the lowest shares in the state (exhibit 4). Of those two, Sacramento–Roseville–Arden–Arcade is one of the rule areas, whereas Los Angeles–Long Beach is not. Both areas are in California where the state’s legislative analyst’s office proclaimed a statewide under-production of housing by 100,000 units, severely impacting the availability of units (Alamo and Uhler, 2015), underlining the importance of supply-side issues as well to the success of the HUD program.

Notably, there is considerable variation with respect to availability even within high-cost areas. For the San Francisco Bay Area, core FMR areas differ considerably in their placement, with San Francisco having around 21 percent of units below FMR levels, while San Jose lands closer to the national average, at 39 percent. Seattle has above-average unit availability, suggesting that it is not simply a matter of the FMR methodology being unable to capture price increases in coastal tech-based economies: here, San Francisco and San Jose differ in how they perform on the FMR score, perhaps due to San Francisco’s long-standing rent control policy, which could downward bias the payment standard.¹⁴

¹⁴ At the same time, it is conceivable rent control could upward bias FMR levels for a region insofar as the recent mover adjustment based on 1-year ACS data in the numerator is compared to the baseline rent data based on 5-year ACS data in the denominator. Rent control would likely impact the denominator more, leading to a larger upwards adjustment per the recent mover adjustment factor.

Exhibit 4

Share of Listings, Top 50 CBSAs Below FMR



CBSA = Core-Based Statistical Areas. FMR = Fair Market Rent. MSA = Metropolitan Statistical Area.
 Notes: For the top 50 CBSAs by population, the share of listings falling below FMRs. CBSAs in the 24 Rule Areas marked in red.
 Sources: Rental listings from Craigslist; FMR/SAFMR data from HUD

To better appreciate the nature of the transition to SAFMRs in a spatial sense, exhibit 5 shows, at the ZCTA level of aggregation, the difference between FMR and SAFMRs for the 24 Rule Areas. Negative values, from the left side of the key, show that SAFMRs are *below* the FMR for the subarea, so subsidy payments for units in these areas will go down. The right side of the key denotes an *increase* in subsidy payments.

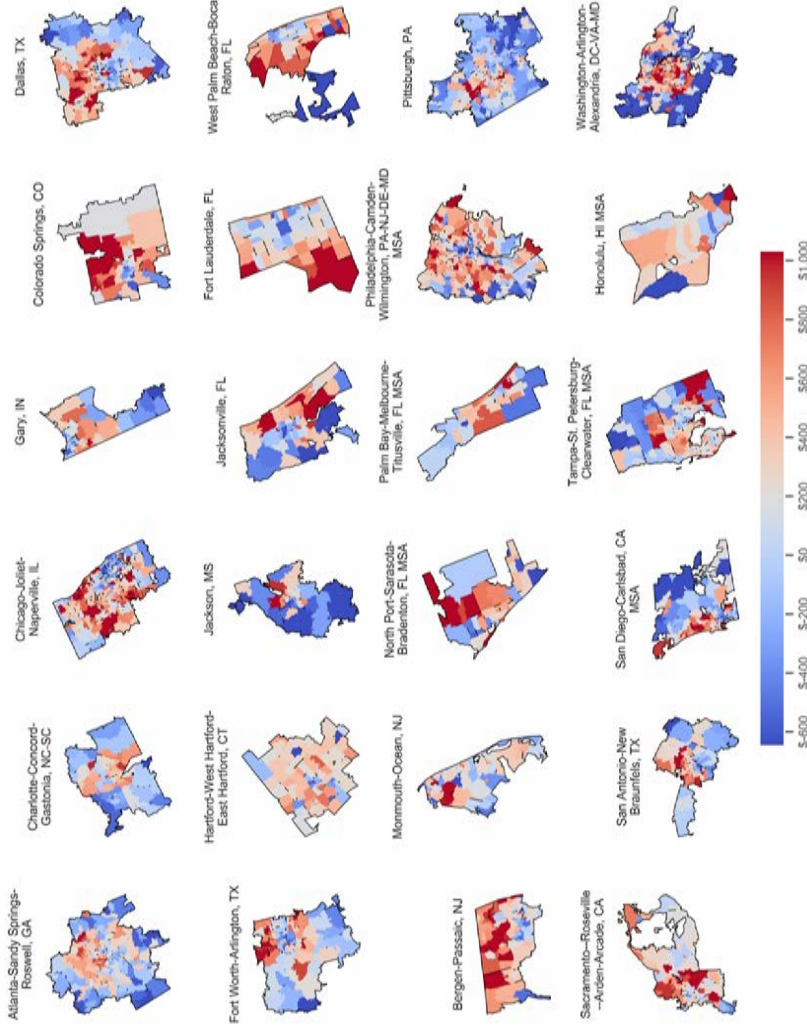
Overall, the map serves to illustrate the variety of submarkets in each region. In San Diego, for example, coastal areas tend to be the most expensive and inland areas the least, reflecting considerable geographic differences in rental costs; this is tracked more closely by a finer-grained SAFMR standard. Importantly, the submarket-specific location of listings and associated rents on those maps will determine the shift of the overall count of listings below FMR levels. If a plurality of units happens to fall in low-cost areas with a lower payment standard, it would lower the count

available below FMR level. Conversely, more units in high-cost areas would mean an overall increase in units available below FMR levels.

While the SAFMR data has been made available for a few years, making it possible to compare the specific areas of change (exhibit 5), those maps only tell a partial story. Areas that may *appear* to see dramatic changes in FMR levels may turn out to lead to ultimately modest changes if few rental units exist there, or if turnover is low. The address-level geographic specificity and ultimately microdata-nature of Craigslist data provides literal weights to those maps, telling us about where listings are, how much they rent for, and where any one particular listing falls in the price brackets defined by both the conventional FMR geography as well as by the potential SAFMR geographies. For example, a listing in an above-average price neighborhood may have been above FMR levels in the area-level schema and thus likely out of reach, but below SAFMR levels in the ZIP Code-based schema. That same listing can be accounted for as having “transitioned” from out of reach to within reach on monetary terms alone. We leverage the microdata nature of the data to analyze those transitions by comparing geocoded listing rents with both the areawide FMRs as well as with the SAFMRs. We subtract FMRs from the listing rent, where 0 means parity, positive means the listing is above (out of reach) FMR levels, and negative means it falls below FMR levels.

Exhibit 5

Difference at ZCTA Level, FMR to SAFMR, in Dollars, for 24 Rule Areas

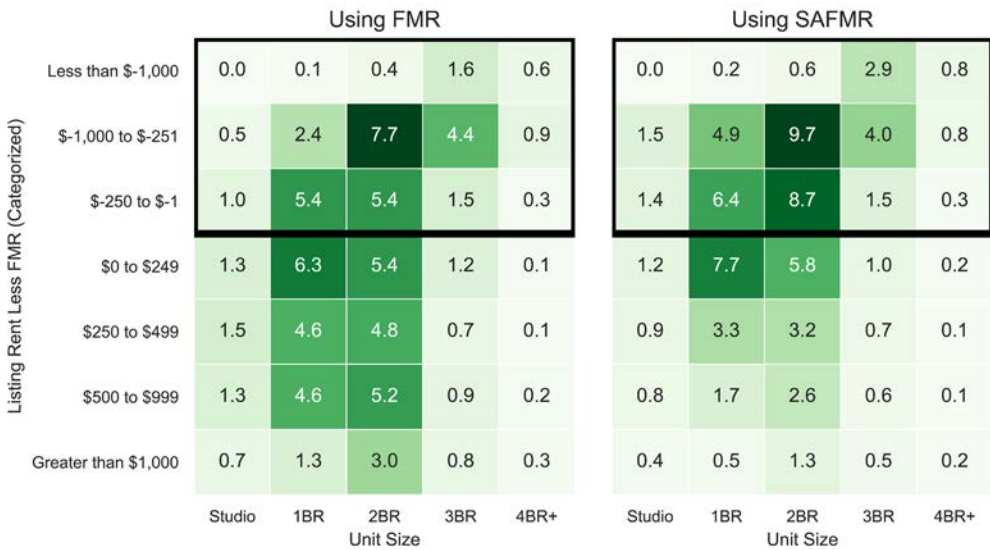


FMR = Fair Market Rent. SAFMR = Small Area Fair Market Rent. ZCTA = Zip Code Tabulation Area.
 Note: Maps show ZCTA-level differences between SAFMRs and FMRs, which in effect is the same as the ratio of the ZCTA-level rent to the FMR-level rent, per HUD's methodology.
 Sources: FMR/SAFMR data from HUD; ZCTA shapefile from U.S. Census Bureau

As an example of how a particular area has seen a change in the distribution of listings as SAFMRs were introduced, exhibit 6 shows the shift in units for San Diego, one of the 24 Rule Areas. We see a shift of listings in the lower, pricier rows in the figure where rents are well above FMR levels, to higher ones with SAFMR. Particularly for San Diego, we see a substantial upward shift in the availability of one-bedroom units, owing to listings in areas that are now subject to the higher SAFMRs.

Exhibit 6

Example Distributions, San Diego FMR Area



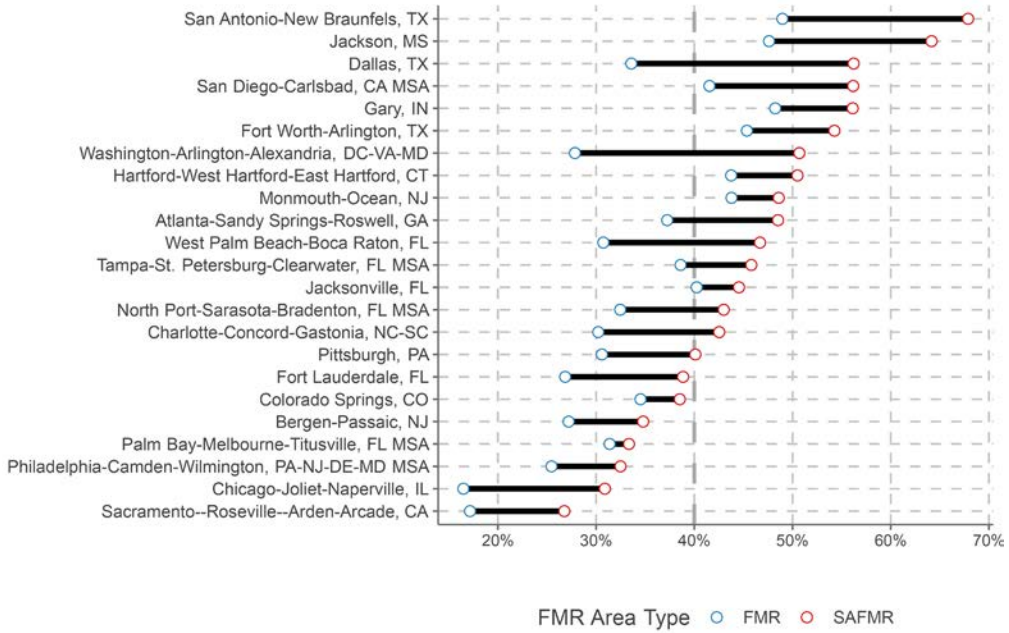
BR = Bedroom. FMR = Fair Market Rent. SAFMR = Small Area Fair Market Rent.

Notes: Listings in thousands. The y-axis is listing rent minus FMR level (left panel) or SAFMR level (right panel). Positive categories (bottom three rows) means the listing rent for more than the prevailing FMR level; the top three rows, marked by a black rectangle, indicate listings costing less than the prevailing FMR level. Labels show count, in thousands, of listings.

To see the general distribution for the 24 Rule Areas, exhibit 7 shows the areas sorted by share below SAFMR in percentage points below the respective FMR level (FMR and SAFMR). The span between the dots shows the movement for each area. The overall impression is that a SAFMR transition for the 24 Rule Areas leads to a larger share of units falling below FMR levels and thereby being, in principle, accessible to voucher holders, while there is considerable between-area variation. Just 6 of the 24 Rule Areas have less than 40 percent of listings available below SAFMR, with Sacramento remaining in the bottom of the list. While SAFMRs shifted availability upwards by nearly 20 percentage points, the levels are substantially lower than what was reported using 2012–2013 data, whether due to inflation or data source coverage differences (Palm, 2018). Overall, however, as far as the basis for the payment standard goes, the number of units and areas available to voucher holders has increased.

Exhibit 7

HUD Final Rule Areas, Overall Shift in Share of Listings Below FMRs



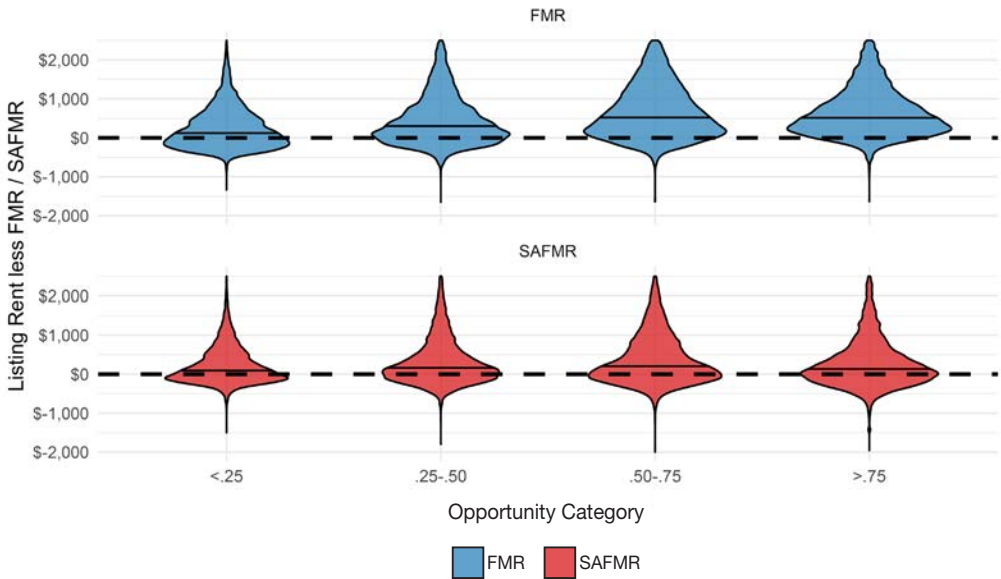
FMR = Fair Market Rent. MSA = Metropolitan Statistical Area. SAFMR = Small Area Fair Market Rent.
 Note: The length of the line denotes the movement in percentage points of listings falling below FMRs in each classification.
 Sources: Rental listings from Craigslist; FMR/SAFMR data from HUD

Effect by Opportunity Areas

How are listing rents relative to FMRs and SAFMRs distributed, and what is the relation to neighborhoods of opportunity? Exhibit 8 compares the distribution of listings in FMR areas but also under SAFMRs.

Exhibit 8

Distribution of Listing-Level Difference, to FMR and SAFMR, by Opportunity Index Category

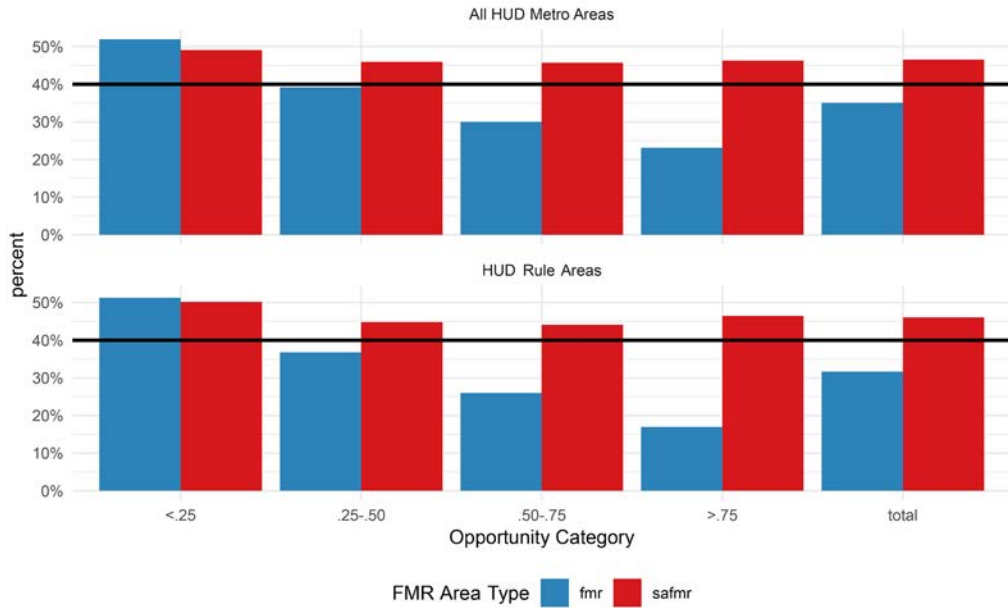


FMR = Fair Market Rent. SAFMR = Small Area Fair Market Rent.
 Sources: Rental listings from Craigslist; FMR/SAFMR data from HUD

For each listing, the difference to the applicable FMR is calculated. Zero means parity; a positive value means the Craigslist listing is *more* expensive than the FMR; a negative one means it is priced below FMR. We further segment the data into four different opportunity categories. Each listing inherits the score from the containing census tract. Scores are quartiles at the tract level, but not necessarily at the rental listing level, and a panel is devoted to each segment. The left panel of the top row shows that for MAFMR areas, much of the distribution is below the zero line, meaning that listings are typically available at the fair market rent level on offer. The bottom row shows the listings classified according to SAFMR geographies. As we head rightward in the figure, toward higher opportunity areas, the share of units below parity generally drops: fewer units have traditionally been affordable to voucher holders in higher opportunity neighborhoods. This is most noticeable in the top row, with FMRs. The bottom row reveals that, with the SAFMR classification, as we move to higher opportunity categories, the number of units falling below parity *declines much less* than is the case in the top row: as the payment standard goes up in more costly, higher opportunity areas, listings are counted as reachable.

Exhibit 9

Share of Listings Above FMR Limits, FMR and SAFMR Variants, by Opportunity Index Category



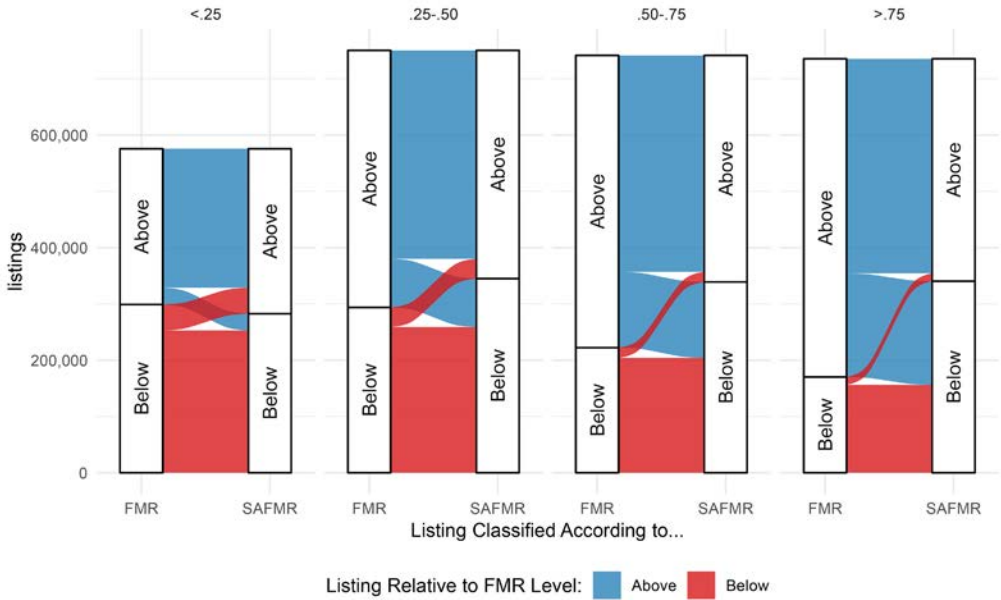
FMR = Fair Market Rent. SAFMR = Small Area Fair Market Rent.
 Sources: Rental listings from Craigslist; FMR/SAFMR data from HUD

Whereas exhibit 8 showed distributions of the difference between FMR levels and rent levels by opportunity category, exhibit 9 shows the number of listings by opportunity category as percentages above or below FMR levels. The top panel accounts for just the 24 Rule Areas, whereas the bottom panel shows the full national sample. As before, there is a clear progression from low to high opportunity categories, with relatively fewer units available, and, within each opportunity quartile, relatively more listings are available in the SAFMR classification. The 24 Rule Areas differ mainly from the national sample in availability per FMR; overall, SAFMR availability shows a remarkable constancy even as we move up opportunity categories. While this may seem a remarkable shift, it just reflects that the payment standard goes up, following higher cost areas more closely.

The last way we explore listings by opportunity areas allows us to track explicitly the number of units changing “state,” from above FMR, or unattainable, to below SAFMR, by showing flows as ribbons from one distribution to the next.

Exhibit 10

Listings, by Change of Status, to Above / Below FMR Level, by Opportunity Category

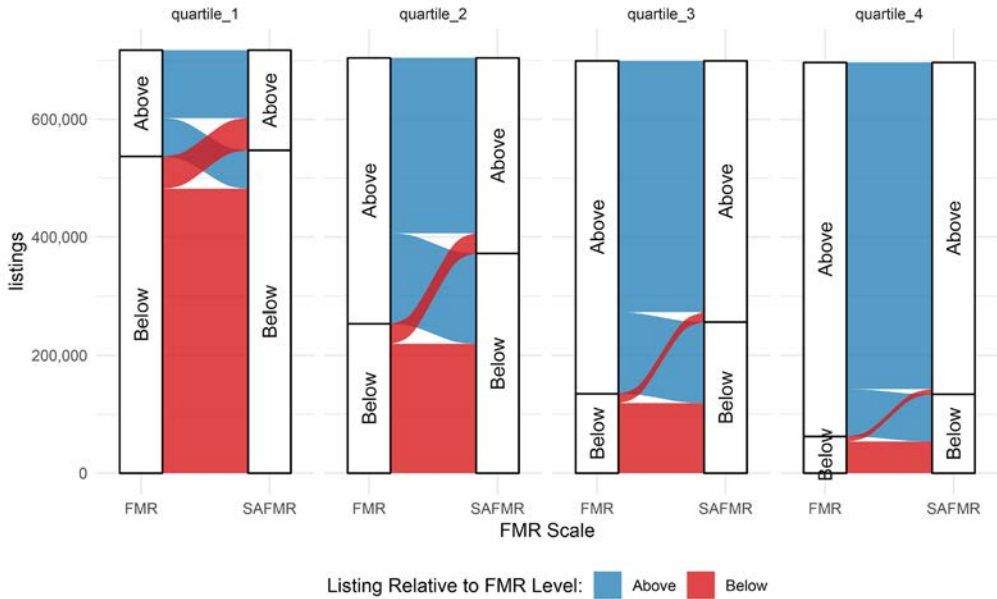


FMR = Fair Market Rent. SAFMR = Small Area Fair Market Rent.
 Sources: Rental listings from Craigslist; FMR/SAFMR data from HUD

The ribbons show the scale of that transition, with the width of the ribbon proportional to the number of units being reclassified from above FMR to below FMR levels (exhibit 10). Notably, the middle categories covering the 25th to 75th percentile opportunity area bands show that a lot of units are above the FMR, meaning many units are off-limits. At the same time, the ribbon shows a considerable transition of listings into the *below* SAFMR bucket: Nationally, about 14 percent of listings switch from being unavailable to available in mid- and high-opportunity areas. The bands of key interest are those that originate in “above” but transition to “below,” and the biggest switch appears in the higher opportunity areas on the right, with a substantial number of units that transition from above to below FMR levels with SAFMRs.

Exhibit 11

Listings, by Change of Status, to Above / Below FMR Level, by Rent Quartile Category



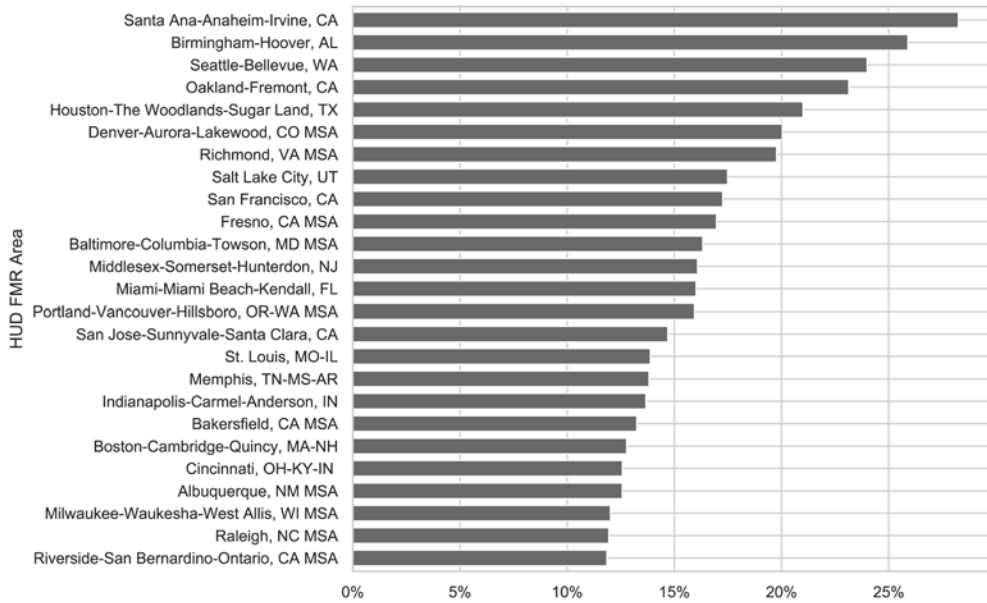
FMR = Fair Market Rent. SAFMR = Small Area Fair Market Rent.
 Sources: Rental listings from Craigslist; FMR/SAFMR data from HUD

Exhibit 11 is analogous to exhibit 10 but instead of segmenting by opportunity category, we show the rental price quartile calculated within each metropolitan area. Overall, the progression from quartile one through four is fairly marked: There are progressively fewer units below FMR levels as we move up the rental cost distribution. Note the transition from above to below FMRs is about equivalent to the transition in the reverse direction for the first quartile. In the second quartile, this is no longer true, and a substantial number of units becomes available below SAFMRs. Similar to what we saw with higher opportunity areas, higher listing price areas, by definition, will have fewer units below the FMR, although SAFMRs still offer more units than would be the case with the areawide FMR system.

While SAFMRs have been applied to a limited number of areas, in part due to concerns related to negative consequences in areas where the payment standard would be lowered, it is nonetheless instructive to briefly explore non-rule areas where considerable counts of listings would switch to being below FMR levels per the new SAFMR system. To do this, we examined non-rule areas with respect to the transition. Of the top 50 FMR non-rule areas by population, we show the top 25 non-rule FMR areas sorted by the percentage point of listings moving to below FMR levels subtracting any units that fell *above* the threshold.

Exhibit 12

Biggest Net Increase of Listings Below FMR, Non-Rule FMR Areas



FMR = Fair Market Rent. MSA = Metropolitan Statistical Area.

Notes: Net increase compares listings that move "ABOVE FMR" levels and listings that move "BELOW FMR" levels, assuming SAFMRs were applied. The areas with the largest net gains in listing counts are shown.

The Santa Ana-Anaheim-Irvine, California FMR Area tops the list, with more than one-fourth of its listings crossing the threshold to be reachable below the FMR level. The Seattle-Bellevue, Washington and Oakland-Fremont, California FMR areas are in the top five, as is Houston-The Woodlands-Sugarland, Texas, and Birmingham-Hoover, Alabama. The lowest increase on this top 25 list is Riverside-San Bernardino-Ontario, California, with about 12 percent of units transitioning. Overall, the list contains a diverse array of areas and economies, spanning the country, but with the strongest gains seen in some of the more dynamic regional economies. We found a small but positive association between areas with higher personal incomes per capita and the share of listings transitioning to falling below FMRs. Future work should explore which particular characteristics account for this finding.

Discussion

This research uses listing data from Craigslist to offer insights into the transition to SAFMRs for both the 24 Rule Areas and FMR areas more generally. While the data come with a range of limitations due to their nature as a VGI dataset subject to a number of quality control issues, the data have the advantage of currency and granularity and they also represent what a would-be tenant could actually see when searching for an apartment.

We found that a switch to SAFMRs, consistent with earlier studies and objectives of the program, increases the count of units available in higher cost and higher opportunity areas. While further investigation is needed to better understand the downsides and risks, let alone the considerable variation in benefits associated with transitioning to finer scaled geographies for different types of areas, these findings suggest the switch to SAFMRs could generally prove beneficial not just for the 24 Rule Areas required to use SAFMR as the basis for setting payment standards, but indeed for a larger swath of FMR areas where high costs have persistently been an issue.

The switch to SAFMRs led to a boost of listings available in generally higher opportunity areas with only a relatively minor loss of availability in low opportunity areas. On its face, the upside was considerable, with the highest opportunity area category seeing more than 45 percent of listings falling below SAFMR levels. While this boost was largest for the 24 Rule Areas, it was nonetheless significant for non-rule areas as well, with solid boosts in availability for a range of generally higher cost areas; those areas included the tech hotspots of Seattle, Denver, and the San Francisco Bay Area. Before a wider rollout, it goes without saying that careful safeguards should be included to avoid disruption of *existing* households in areas where payment standards would drop, causing risk to renewals. If the voucher opportunity map changes as implied, and lease-ups in these wider areas prove successful in the coming years, local PHAs may find budgets even more strained, barring more resources to the program overall.

Longer Term Challenges

In many ways, the HCV program shows the limits both of a housing policy heavily focused on demand-side solutions and of how variable the outcomes of the program are. That is not because the program treats FMR areas differently but because FMR areas have substantially different housing markets. The hot coastal markets are much more difficult to fix with demand-side measures when the challenge is a complex mix of low incomes, low supply, and spillover effects from well-to-do tenants. The most critical need is in the areas with the most constrained rental markets where rents are high and availability accordingly low. This is the typical situation in the hot coastal markets, such as Los Angeles and the San Francisco Bay area, where vacancies are low and talk of housing crises perennial. In those cases, the bottom of the housing market cannot be easily remedied with an administrative fix and realignment like SAFMRs. As one PHA official put it, landlords have a choice of tenants, and with rental vacancies hovering around perhaps 2 percent, landlords will have many options to rapidly fill their units without having to face the extra risk, perceived or real, of subsidized tenants. In HUD's phrasing,

[a] major question regarding the Small Area FMR approach is the willingness of owners with rental units in the higher cost areas to participate in the program. If owners in higher-cost areas have enough demand for their units from higher income unassisted families, they may have little interest or incentive to participate in the HCV program (HUD, 2017b).

It was for this reason that some areas that would otherwise seem great candidates for inclusion in the SAFMR version of the program balked—low vacancies would effectively preclude success and could end up wasting money at the top of the rental distribution while causing disruption for lower-income tenants. Ultimately, in those types of areas where the need may be the greatest, the

restrictive supply regime of the expensive coastal areas will remain an impediment to a successful housing policy framework across levels of government—although SAFMRs appear to be a great methodological realignment to allocate scarce resources to higher opportunity areas while limiting landlord subsidies in lower cost submarkets. Whether the program adjustment will be successful and actually translate the increased availability listings reachable by the program into higher lease-up success rates in high-opportunity areas remains to be seen in the coming years. The 24 Rule Areas may in effect help us understand more about the extent to which difficulties leasing up in higher opportunity neighborhoods were of the financial sort, or instead related to a wider set of issues, such as search costs, transportation challenges, or landlord behavior.

Acknowledgments

The author is indebted to Paul Waddell and Geoff Boeing for sharing data and insights on Craigslist data, and to the *Cityscape* reviewers and editors for helpful comments that improved the paper. This work was supported in part by a Doctoral Completion Fellowship at UC Berkeley. The views expressed in this article are those of the author and are not necessarily those of the Association of Bay Area Governments or the Metropolitan Transportation Commission.

Author

Aksel Olsen is currently a senior planner at the Association of Bay Area Governments and Metropolitan Transportation Commission in San Francisco, California. He can be reached at aolsen@bayareametro.gov.

Data Appendix

The data appendix provides key summaries by FMR area of the filtered listings data, including the number of listings, mean or median bedroom counts, asking rent, and rent per square foot. The tables also show the difference between listing rent and MAFMR and SAFMR, respectively. A positive number means the listing rent is above the FMR; a negative means below. The median of this difference is provided. The last four columns show the effect of the transition; the four columns sum to 100 percent and show the four possible states: A listing could be, for MAFMRs and SAMFRs in turn, available or not available at that price point. Some listings would be available or not under both systems, while others would transition to becoming either available or not available.

The two tables differ only in terms of areas covered: exhibit A1 shows the 24 Rule Areas, whereas exhibit A2 presents data for the top 50 (by population) non-rule FMR areas.

Appendix A: Additional Exhibits

Exhibit A.1

Summary Statistics and Transitions for 24 Rule Areas (1 of 2)

FMR Area	Listings (Count)	Sq Ft (Median)	Bedrooms (Mean)	Rent (Median)	Rent/Sq Ft (Mean)	Rent Less FMR (Median)	Rent Less SAFMR (Median)	Listing Transitions			
								Out of Reach in Both Systems	Became Within Reach	Became Out of Reach	Within Reach in Both Systems
Atlanta-Sandy Springs-Roswell, GA HUD Metro FMR Area	47,066	1,100	1.9	\$1,239	\$1.1	\$128	\$3	48%	15%	4%	34%
Bergen-Passaic, NJ HUD Metro FMR Area	3,096	1,003	1.8	\$2,095	\$1.9	\$513	\$267	62%	11%	3%	24%
Charlotte-Concord-Gastonia, NC-SC HUD Metro FMR Area	21,640	1,034	1.8	\$1,195	\$1.1	\$148	\$45	54%	16%	4%	26%
Chicago-Joliet-Naperville, IL HUD Metro FMR Area	78,567	900	1.6	\$1,700	\$1.9	\$553	\$225	67%	16%	2%	15%
Colorado Springs, CO HUD Metro FMR Area	13,724	936	1.8	\$1,192	\$1.2	\$136	\$55	51%	14%	10%	24%
Dallas, TX HUD Metro FMR Area	61,128	925	1.6	\$1,270	\$1.3	\$154	-\$52	41%	25%	3%	31%
Fort Lauderdale, FL HUD Metro FMR Area	24,366	1,151	2.1	\$1,800	\$1.5	\$265	\$105	59%	14%	2%	25%
Fort Worth-Arlington, TX HUD Metro FMR Area	18,485	920	1.8	\$1,037	\$1.1	\$27	-\$25	39%	16%	7%	39%
Gary, IN HUD Metro FMR Area	2,243	996	2.1	\$905	\$0.9	\$9	-\$30	40%	11%	4%	45%
Hartford-West Hartford-East Hartford, CT HUD Metro FMR Area	5,486	1,000	1.9	\$1,200	\$1.1	\$40	-\$12	46%	10%	3%	40%
Jackson, MS HUD Metro FMR Area	2,260	1,130	2.2	\$900	\$0.8	\$10	-\$90	32%	21%	4%	44%
Jacksonville, FL HUD Metro FMR Area	17,069	1,081	1.9	\$1,050	\$1.0	\$96	\$30	51%	9%	5%	35%

Exhibit A.1**Summary Statistics and Transitions for 24 Rule Areas (2 of 2)**

FMR Area	Listings (Count)	Sq Ft (Median)	Bedrooms (Mean)	Rent (Median)	Rent/Sq Ft (Mean)	Rent Less FMR (Median)	Rent Less SAFMR (Median)	Listing Transitions			
								Out of Reach in Both Systems	Became Within Reach	Became Out of Reach	Within Reach in Both Systems
Monmouth-Ocean, NJ HUD Metro FMR Area	2,062	1,055	2.1	\$1,500	\$1.3	\$71	\$10	49%	7%	2%	42%
North Port-Sarasota-Bradenton, FL MSA	6,822	1,103	2.0	\$1,299	\$1.2	\$115	\$40	52%	15%	5%	28%
Palm Bay-Melbourne-Titusville, FL MSA	3,251	1,104	2.1	\$1,275	\$1.1	\$208	\$155	62%	6%	4%	27%
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD MSA	38,379	975	1.8	\$1,472	\$1.5	\$325	\$160	63%	11%	4%	21%
Pittsburgh, PA HUD Metro FMR Area	11,148	950	1.8	\$1,015	\$1.1	\$175	\$70	57%	12%	3%	28%
Sacramento-Roseville-Arden-Arcade, CA HUD Metro FMR Area	30,720	975	1.9	\$1,550	\$1.5	\$327	\$185	71%	12%	2%	15%
San Antonio-New Braunfels, TX HUD Metro FMR Area	28,097	908	1.7	\$989	\$1.1	\$2	-\$102	30%	21%	2%	47%
San Diego-Carlsbad, CA MSA	77,357	910	1.8	\$2,050	\$2.2	\$105	-\$70	34%	25%	10%	31%
Tampa-St. Petersburg-Clearwater, FL MSA	32,110	1,028	1.9	\$1,205	\$1.2	\$84	\$24	50%	11%	4%	35%
Washington-Arlington-Alexandria, DC-VA-MD HUD Metro FMR Area	103,205	882	1.5	\$1,853	\$2.1	\$276	-\$13	46%	26%	3%	25%
West Palm Beach-Boca Raton, FL HUD Metro FMR Area	17,416	1,224	2.2	\$1,725	\$1.4	\$200	\$20	50%	19%	3%	28%

FMR = Fair Market rent, MSA = Metropolitan Statistical Area, SAFMR = Small Area Fair Market Rent.

Exhibit A.2

Summary Statistics and Transitions for Top 50 (by Population) Non-Rule FMR Areas (1 of 4)

FMR Area	Listings (Count)	Sq Ft (Median)	Bedrooms (Mean)	Rent (Median)	Rent/Sq Ft (Mean)	Rent Less FMR (Median)	Rent Less SAFMR (Median)	Listing Transitions			
								Out of Reach in Both Systems	Became Within Reach	Within Reach in Both Systems	
Albuquerque, NM MSA	14,288	855	1.7	\$810	\$1.0	-\$13	-\$64	32%	15%	3%	50%
Austin-Round Rock, TX MSA	62,621	900	1.7	\$1,291	\$1.4	\$35	-\$30	42%	13%	5%	41%
Bakersfield, CA MSA	3,178	1,000	2.1	\$950	\$0.9	-\$31	-\$120	30%	17%	4%	49%
Baltimore-Columbia-Towson, MD MSA	25,421	1,000	1.8	\$1,475	\$1.4	\$176	-\$11	48%	18%	2%	33%
Birmingham-Hoover, AL HUD Metro FMR Area	4,005	1,075	2.0	\$925	\$0.9	\$40	-\$128	31%	29%	3%	38%
Boston-Cambridge-Quincy, MA-NH HUD Metro FMR Area	63,525	950	1.9	\$2,540	\$2.7	\$403	\$145	55%	17%	5%	23%
Brockton, MA HUD Metro FMR Area	528	1,000	2.1	\$1,599	\$1.4	\$154	\$129	60%	7%	3%	30%
Buffalo-Cheektowaga-Niagara Falls, NY MSA	7,250	1,040	2.1	\$950	\$0.9	\$87	\$60	57%	8%	4%	31%
Cincinnati, OH-KY-IN HUD Metro FMR Area	12,048	1,000	2.0	\$927	\$0.9	\$50	-\$30	43%	16%	3%	39%
Cleveland-Elyria, OH MSA	10,115	1,050	2.1	\$900	\$0.9	\$31	\$0	46%	9%	5%	40%
Columbus, OH HUD Metro FMR Area	16,254	1,000	1.9	\$1,000	\$1.0	\$107	\$30	51%	14%	4%	31%
Danbury, CT HUD Metro FMR Area	710	1,000	1.7	\$1,650	\$1.5	\$317	\$270	66%	5%	1%	28%
Denver-Aurora-Lakewood, CO MSA	97,588	900	1.6	\$1,562	\$1.7	\$167	-\$20	45%	24%	3%	28%
Detroit-Warren-Livonia, MI HUD Metro FMR Area	19,891	1,030	2.1	\$1,002	\$1.0	\$73	\$19	49%	9%	4%	38%
Fresno, CA MSA	8,864	1,026	2.1	\$1,225	\$1.1	\$144	\$15	52%	18%	1%	29%

Exhibit A.2

Summary Statistics and Transitions for Top 50 (by Population) Non-Rule FMR Areas (2 of 4)

FMR Area	Listings (Count)	Sq Ft (Median)	Bedrooms (Mean)	Rent (Median)	Rent/Sq Ft (Mean)	Rent Less FMR (Median)	Rent Less SAFMR (Median)	Listing Transitions			
								Out of Reach in Both Systems	Became Within Reach	Became Out of Reach	Within Reach in Both Systems
Houston-The Woodlands-Sugar Land, TX HUD Metro FMR Area	49,073	933	1.7	\$1,110	\$1.2	\$53	-\$110	32%	24%	3%	40%
Indianapolis-Carmel-Anderson, IN HUD Metro FMR Area	12,853	997	1.8	\$860	\$0.9	-\$28	-\$86	27%	17%	3%	53%
Kansas City, MO-KS HUD Metro FMR Area	15,546	954	1.8	\$900	\$1.0	-\$13	-\$45	39%	10%	4%	47%
Las Vegas-Henderson-Paradise, NV MSA	46,922	1,000	1.8	\$1,129	\$1.1	\$134	\$70	57%	8%	4%	31%
Los Angeles-Long Beach-Glendale, CA HUD Metro FMR Area	129,255	910	1.6	\$2,299	\$2.6	\$704	\$390	76%	12%	2%	11%
Louisville, KY-IN HUD Metro FMR Area	10,163	950	1.9	\$865	\$0.9	\$31	-\$5	47%	10%	2%	40%
Memphis, TN-MS-AR HUD Metro FMR Area	7,502	1,034	2.1	\$840	\$0.8	-\$143	-\$195	25%	15%	1%	59%
Miami-Miami Beach-Kendall, FL HUD Metro FMR Area	47,317	1,030	1.8	\$1,950	\$2.0	\$548	\$240	66%	18%	2%	13%
Middlesex-Somerset-Hunterdon, NJ HUD Metro FMR Area	4,370	1,088	1.8	\$1,800	\$1.6	\$149	\$25	49%	20%	4%	28%
Milwaukee-Waukesha-West Allis, WI MSA	12,691	1,000	1.9	\$1,095	\$1.1	\$152	\$55	56%	14%	2%	28%
Minneapolis-St. Paul-Bloomington, MN-WI HUD Metro FMR Area	37,323	970	1.8	\$1,420	\$1.4	\$314	\$195	69%	9%	2%	19%
Nashville-Davidson-Murfreesboro-Franklin, TN HUD Metro FMR Area	21,831	1,050	1.9	\$1,273	\$1.2	\$147	\$58	56%	11%	2%	31%
Nassau-Suffolk, NY HUD Metro FMR Area	3,846	1,043	1.8	\$2,250	\$2.0	\$410	\$265	64%	6%	2%	27%
New Orleans-Metairie, LA HUD Metro FMR Area	10,239	1,000	1.9	\$1,100	\$1.2	\$92	\$10	51%	11%	2%	36%

Exhibit A.2

Summary Statistics and Transitions for Top 50 (by Population) Non-Rule FMR Areas (3 of 4)

FMR Area	Listings (Count)	Sq Ft (Median)	Bedrooms (Mean)	Rent (Median)	Rent/Sq Ft (Mean)	Rent Less FMR (Median)	Rent Less SAFMR (Median)	Listing Transitions			
								Out of Reach in Both Systems	Became Within Reach	Within Reach in Both Systems	
New York, NY HUD Metro FMR Area	28,919	850	1.7	\$2,550	\$3.1	\$675	\$450	9%	74%	3%	14%
Newark, NJ HUD Metro FMR Area	4,356	1,000	1.9	\$1,775	\$1.6	\$387	\$130	12%	60%	3%	26%
Oakland-Fremont, CA HUD Metro FMR Area	50,763	898	1.8	\$2,500	\$2.6	\$422	\$100	24%	58%	1%	18%
Oklahoma City, OK HUD Metro FMR Area	14,851	960	1.9	\$775	\$0.8	-\$111	-\$140	11%	21%	2%	66%
Orlando-Kissimmee-Sanford, FL MSA	27,223	1,079	2.0	\$1,319	\$1.2	\$125	\$47	12%	54%	3%	31%
Phoenix-Mesa-Scottsdale, AZ MSA	60,433	952	1.8	\$1,129	\$1.1	\$87	\$10	15%	48%	6%	32%
Portland-Vancouver-Hillsboro, OR-WA MSA	81,347	915	1.8	\$1,445	\$1.6	\$0	-\$115	18%	33%	2%	48%
Providence-Fall River, RI-MA HUD Metro FMR Area	9,001	1,000	2.0	\$1,400	\$1.3	\$340	\$235	7%	70%	3%	20%
Raleigh, NC MSA	15,441	1,070	1.9	\$1,129	\$1.1	\$46	-\$26	14%	45%	2%	40%
Richmond, VA MSA	13,859	940	1.9	\$1,125	\$1.2	\$63	-\$61	22%	37%	3%	38%
Riverside-San Bernardino-Ontario, CA MSA	33,854	1,000	2.1	\$1,670	\$1.5	\$438	\$150	15%	66%	3%	17%
Rochester, NY HUD Metro FMR Area	8,403	1,090	2.0	\$1,100	\$1.1	\$145	\$55	9%	57%	3%	31%

Exhibit A.2

Summary Statistics and Transitions for Top 50 (by Population) Non-Rule FMR Areas (4 of 4)

FMR Area	Listings (Count)	Sq Ft (Median)	Bedrooms (Mean)	Rent (Median)	Rent/Sq Ft (Mean)	Rent Less FMR (Median)	Rent Less SAFMR (Median)	Listing Transitions			
								Out of Reach in Both Systems	Became Within Reach	Became Out of Reach	Within Reach in Both Systems
Salt Lake City, UT HUD Metro FMR Area	14,247	899	1.7	\$1,159	\$1.3	\$132	\$45	56%	20%	2%	23%
San Francisco, CA HUD Metro FMR Area	47,456	870	1.6	\$3,450	\$3.8	\$530	\$143	55%	19%	2%	24%
San Jose-Sunnyvale-Santa Clara, CA HUD Metro FMR Area	46,972	935	1.8	\$2,899	\$3.0	\$157	-\$76	41%	20%	5%	35%
Santa Ana-Anaheim-Irvine, CA HUD Metro FMR Area	57,545	950	1.7	\$2,087	\$2.2	\$188	-\$35	41%	34%	6%	19%
Seattle-Bellevue, WA HUD Metro FMR Area	130,398	820	1.5	\$1,850	\$2.2	\$112	-\$165	32%	26%	2%	39%
St. Louis, MO-IL HUD Metro FMR Area	19,106	935	1.8	\$900	\$1.0	\$26	-\$50	40%	15%	1%	44%
Tucson, AZ MSA	21,892	810	1.7	\$795	\$1.0	-\$28	-\$55	33%	12%	3%	52%
Virginia Beach-Norfolk-Newport News, VA-NC HUD Metro FMR Area	15,806	1,000	1.9	\$1,123	\$1.1	-\$14	-\$96	37%	11%	2%	50%
Westchester County, NY Statutory Exception Area	2,907	942	1.7	\$2,197	\$2.2	\$422	\$265	70%	12%	4%	14%

FMR = Fair Market Rent. MSA = Metropolitan Statistical Area. SAFMR = Small Area Fair Market Rent.

References

- Alamo, Chas, and Brian Uhler. 2015. *California's High Housing Costs - Causes and Consequences*. Sacramento, CA: State of California.
- Bayer, Patrick, Robert McMillan, Alvin Murphy, and Christopher Timmins. 2016. "A Dynamic Model of Demand for Houses and Neighborhoods," *Econometrica* 84 (3): 893–942. <https://doi.org/10.3982/ECTA10170>.
- Berkeley Housing Authority. 2019. "Housing Choice Voucher Program (Section 8) Waiting List." https://www.cityofberkeley.info/BHA/Home/Section_8_Wait_List.aspx.
- Boeing, Geoff, and Paul Waddell. 2017. "New Insights into Rental Housing Markets across the United States: Web Scraping and Analyzing Craigslist Rental Listings," *Journal of Planning Education and Research* 37 (4): 457–476. <https://doi.org/10.1177/0739456X16664789>.
- Bourassa, Steven C., Foort Hamelink, Martin Hoesli, and Bryan D. MacGregor. 1999. "Defining Housing Submarkets," *Journal of Housing Economics* 8 (2): 160–183. <https://doi.org/10.1006/jhec.1999.0246>.
- Briggs, Xavier De Souza, Jennifer Comey, and Gretchen Weismann. 2010. "Struggling to Stay out of High-Poverty Neighborhoods: Housing Choice and Locations in Moving to Opportunity's First Decade," *Housing Policy Debate* 20 (3): 383–427. <https://doi.org/10.1080/10511481003788745>.
- Chetty, Raj, Nathaniel Hendren, and Lawrence F. Katz. 2015. "The Effects of Exposure to Better Neighborhoods on Children: New Evidence from the Moving to Opportunity Experiment," *American Economic Review* 106 (4): 1–88. <https://doi.org/10.1257/aer.20150572>.
- Collinson, Robert, and Peter Ganong. 2018. "How Do Changes in Housing Voucher Design Affect Rent and Neighborhood Quality?" *American Economic Journal: Economic Policy* 10 (2): 62–89. <https://doi.org/10.1257/pol.20150176>.
- Cunningham, Mary, Martha Galvez, Claudia L. Aranda, Rob Santos, Doug Wissoker, Alyse D. Oneto, R. Pitingolo, and James Crawford. 2018. *A Pilot Study of Landlord Acceptance of Housing Choice Vouchers*. Washington, DC: U.S. Department of Housing and Urban Development.
- Finkel, Meryl, and Larry Buron. 2001. *Volume I Quantitative Study of Success Rates in Metropolitan Areas*. Washington, DC: U.S. Department of Housing and Urban Development.
- Finkel, Meryl, Samuel Dastrup, Kimberly Burnett, Thyria Alvarez, Carissa Climaco, and Tanya de Sousa. 2017. *Small Area Fair Market Rent Demonstration Evaluation: Interim Report*. Washington, DC: U.S. Department of Housing and Urban Development. <https://www.huduser.gov/portal/sites/default/files/pdf/SAFMR-Interim-Report.pdf>.

Fredericks, Rob, and Robert Havlicek. 2017. "Comment Re: Fair Market Rents for the Housing Choice Voucher Program, Moderate Rehabilitation Single Room Occupancy Program, and Other Programs Fiscal Year 2018 and Adoption of Methodology Changes for Estimating Fair Market Rents." Santa Barbara Housing Authority. <https://www.regulations.gov/document?D=HUD-2017-0051-0006>

Galvez, Martha. 2010. *What Do We Know About Housing Choice Voucher Program Location Outcomes?* Washington, DC: Urban Institute, What Works Collaborative.

Goetz, Edward G., and Karen Chapple. 2010. "You Gotta Move: Advancing the Debate on the Record of Dispersal," *Housing Policy Debate* 20 (2): 209–236. <https://doi.org/10.1080/10511481003779876>.

Goodchild, Michael F. 2007. "Citizens as Sensors: The World of Volunteered Geography," *GeoJournal* 69 (4): 211–221. <https://doi.org/10.1007/s10708-007-9111-y>.

Goodspeed, Robert. 2017. "Urban Informatics." In *Big Data for Regional Science*, edited by Laurie A. Schintler and Zhenhua Chen: 324–335. London, UK & New York: Routledge. <https://doi.org/10.4324/9781315270838-27>.

Hwang, Jackelyn, and Jeffrey Lin. 2016. "What Have We Learned About the Causes of Recent Gentrification?" *Cityscape* 18 (3): 9–26.

Khoury, Andrew. 2019. "Housing Vouchers Can Save People from Homelessness. But Landlords May Not Accept Them," *Los Angeles Times*, March 29. <https://www.latimes.com/business/la-fi-section-8-landlords-20190329-story.html>.

Knaap, Gerrit-Jan. 1998. "The Determinants of Residential Property Values: Implications for Metropolitan Planning," *Journal of Planning Literature* 12 (3): 267–282. <https://doi.org/10.1177/088541229801200301>.

Lens, Michael C., Ingrid Gould Ellen, and Katherine O'Regan. 2011. "Do Vouchers Help Low-Income Households Live in Safer Neighborhoods? Evidence on the Housing Choice Voucher Program," *Cityscape* 13 (3): 135–159. <https://www.huduser.gov/portal/periodicals/cityscape/vol13num3/ch6.html>.

McClure, Kirk. 2008. "Deconcentrating Poverty With Housing Programs," *Journal of the American Planning Association* 74 (1): 90–99. <https://doi.org/10.1080/01944360701730165>.

McClure, Kirk, and Bonnie Johnson. 2015. "Housing Programs Fail to Deliver on Neighborhood Quality, Reexamined," *Housing Policy Debate* 25 (3): 463–496. <https://doi.org/10.1080/10511482.2014.944201>.

McClure, Kirk, Alex F. Schwartz, and Lydia B. Taghavi. 2015. "Housing Choice Voucher Location Patterns a Decade Later," *Housing Policy Debate* 25 (2): 215–233. <https://doi.org/10.1080/10511482.2014.921223>.

Myers, Dowell, and Jungho Park. 2019. "A Constant Quartile Mismatch Indicator of Changing Rental Affordability in U.S. Metropolitan Areas, 2000 to 2016," *Cityscape* 21 (1): 163–200. <https://www.huduser.gov/portal/periodicals/cityscape/vol21num1/article7.html>.

Newman, Sandra J., and Ann B. Schnare. 1997. "... And a Suitable Living Environment': The Failure of Housing Programs to Deliver on Neighborhood Quality," *Housing Policy Debate* 8 (4): 703–741. <https://doi.org/10.1080/10511482.1997.9521275>.

New York University (NYU) Furman Center. 2018. "How Do Small Area Fair Market Rents Affect the Location and Number of Units Affordable to Voucher Holders?" New York: NYU Furman Center. http://furmancenter.org/files/NYUFurmanCenter_SAFMRbrief_5JAN2018_1.pdf.

Palm, Matthew. 2018. "Scale in Housing Policy: A Case Study of the Potential of Small Area Fair Market Rents," *Cityscape* 20 (1): 133–152.

Panetta, Jennifer. 2017. "Comment Re: Fair Market Rents for the Housing Choice Voucher Program, Moderate Rehabilitation Single Room Occupancy Program, and Other Programs Fiscal Year 2018 and Adoption of Methodology Changes for Estimating Fair Market Rents." Santa Cruz Housing Authority. <https://www.regulations.gov/document?D=HUD-2017-0051-0011>.

Pendall, Rolf. 2000. "Why Voucher and Certificate Users Live in Distressed Neighborhoods," *Housing Policy Debate* 11 (4): 881–910. <https://doi.org/10.1080/10511482.2000.9521391>.

Rosen, Sherwin. 1974. "Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition," *Journal of Political Economy* 82 (1): 34–55. <https://doi.org/10.1086/260169>.

Ruel, Erin, Deirdre A. Oakley, Chandra Ward, Reneé Alston, and Lesley W. Reid. 2013. "Public Housing Relocations in Atlanta: Documenting Residents' Attitudes, Concerns, and Experiences," *Cities* 35 (December): 349–358. <https://doi.org/10.1016/j.cities.2012.07.010>.

Shroder, Mark. 2002. "Locational Constraint, Housing Counseling, and Successful Lease-up in a Randomized Housing Voucher Experiment," *Journal of Urban Economics* 51 (2): 315–338. <https://doi.org/10.1006/juec.2001.2247>.

Somerville, C. Tsurriel, and Cynthia Holmes. 2001. "Dynamics of the Affordable Housing Stock: Microdata Analysis of Filtering," *Journal of Housing Research* 12 (1): 115–140.

Tighe, J. Rosie, Megan E. Hatch, and Joseph Mead. 2017. "Source of Income Discrimination and Fair Housing Policy," *Journal of Planning Literature* 32 (1): 3–15. <https://doi.org/10.1177/0885412216670603>.

Turner, Margery Austin, and Xavier De Souza Briggs. 2008. *Assisted Housing Mobility and the Success of Low-Income Minority Families: Lessons for Policy, Practice, and Future Research*. Washington, DC: Urban Institute.

U.S. Department of Housing and Urban Development (HUD). 2019. *HUD Resident Characteristics Report*. Washington, DC: U.S. Department of Housing and Urban Development. <https://pic.hud.gov/pic/RCRPublic/rcrmain.asp>.

———. 2018. *Proposals To Update the Fair Market Rent Formula*. Washington, DC: U.S. Department of Housing and Urban Development.

———. 2017a. “Fair Market Rents for the Housing Choice Voucher Program, Moderate Rehabilitation Single Room Occupancy Program, and Other Programs Fiscal Year 2018 and Adoption of Methodology Changes for Estimating Fair Market Rents.” *Federal Register*, Docket No. FR–6021–N–02, 82 (169): 41637–45. <https://www.govinfo.gov/content/pkg/FR-2017-09-01/pdf/2017-18431.pdf>.

———. 2017b. “Notice for Suspension of Small Area Fair Market Rent (Small Area FMR) Designations; Solicitation of Comment.” *Federal Register* 82 (237): 58439–41. <https://www.govinfo.gov/content/pkg/FR-2017-12-12/pdf/2017-26695.pdf>.

———. 2016a. “FR–5855–P–02 Establishing a More Effective Fair Market Rent System; Using Small Area Fair Market Rents in Housing Choice Voucher Program Instead of the Current 50th Percentile FMRs.” *Federal Register* 81 (FR–5855–P–02): 39218–34.

———. 2016b. “Small Area Fair Market Rents in Housing Choice Voucher Program Values for Selection Criteria and Metropolitan Areas Subject to Small Area Fair Market Rents.” *Federal Register*, Docket No. FR–5855–N–04, 81 (221): 80678–79.

———. 2016c. “Establishing a More Effective Fair Market Rent System; Using Small Area Fair Market Rents in the Housing Choice Voucher Program Instead of the Current 50th Percentile FMRs.” *Federal Register* 81. Washington, DC: U.S. Government Printing Office. <https://www.regulations.gov/docket?D=HUD-2016-0063>.

———. 2015. “Proposed Final Fair Market Rents for the Housing Choice Voucher Program, Moderate Rehabilitation Single Room Occupancy Program, and Other Programs; Fiscal Year 2016: A Notice by the Housing and Urban Development Department.” 2015–22023. *Federal Register* Docket No. FR-5885-N-01, 80. Hayward, CA: U.S. Government Printing Office. <https://www.federalregister.gov/documents/2015/09/08/2015-22023/proposed-fair-market-rents-for-the-housing-choice-voucher-program-moderate-rehabilitation-single#h-10>.

———. 2010. “Section 8 Housing Choice Voucher Program-Demonstration Project of Small Area Fair Market Rents in Certain Metropolitan Areas for Fiscal Year 2011.” *Federal Register*. Washington, DC: U.S. Government Printing Office. <https://www.govinfo.gov/content/pkg/FR-2010-05-18/pdf/2010-11731.pdf>.

———. 2000. “Department of Housing and Urban Fair Market Rents : Increased Fair Market.” *Federal Register*. Washington, DC: U.S. Government Printing Office. <https://www.gpo.gov/fdsys/pkg/FR-2000-10-02/pdf/00-24922.pdf>.

Varady, David P., Joseph Jaroscak, and Reinout Kleinhans. 2017. "How to Attract More Landlords to the Housing Choice Voucher Program: A Case Study of Landlord Outreach Efforts," *Urban Research & Practice* 10 (2) 1–13. <https://doi.org/10.1080/17535069.2016.1175741>.

Varady, David P., Xinhao Wang, Yimei Wang, and Patrick Duhaney. 2010. "The Geographic Concentration of Housing Vouchers, Blacks, and Poverty over Time: A Study of Cincinnati, Ohio, USA." *Urban Research & Practice* 3 (1): 39–62. <https://doi.org/10.1080/17535060903534172>.

Villareal, Joseph. 2016. "Comment Re: Department of Housing and Urban Development (HUD) Proposed Rule: FR–5855–P–02 Establishing a More Effective Fair Market Rent System; Using Small Area Fair Market Rents in Housing Choice Voucher Program Instead of the Current 50th Percentile FM." Washington, DC: U.S. Department of Housing and Urban Development. <https://www.regulations.gov/docket?D=HUD-2016-0063>.

Wang, Ruoniu. 2018. "Tracking 'Choice' in the Housing Choice Voucher Program: The Relationship Between Neighborhood Preference and Locational Outcome," *Urban Affairs Review* 54 (2): 302–331. <https://doi.org/10.1177/1078087416646205>.

Wang, Xinhao, and David P. Varady. 2005. "Using Hot-Spot Analysis to Study the Clustering of Section 8 Housing Voucher Families," *Housing Studies* 20 (1): 29–48. <https://doi.org/10.1080/0267303042000308714>.

Watson, Nicole Elsasser, Barry L. Steffen, Marge Martin, and David A. Vandembroucke. 2017. Worst Case Housing Needs - 2017 *Report to Congress*. Washington, DC: U.S. Department of Housing and Urban Development. <https://www.huduser.gov/portal/sites/default/files/pdf/Worst-Case-Housing-Needs.pdf>.

Wiltz, Teresa. 2018. "Getting a Section 8 Voucher Is Hard. Finding a Landlord Willing to Accept It Is Harder," *Stateline*, August 31. <https://www.pewtrusts.org/en/research-and-analysis/blogs/stateline/2018/08/31/getting-a-section-8-voucher-is-hard-finding-a-landlord-willing-to-accept-it-is-harder>.