Cityscape

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Selected Outcomes of Housing Assistance

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Meena Bavan
David Hardiman
U.S. Department of Housing and Urban Development

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This symposium of *Cityscape* presents new information on the primary affordable rental assistance programs of the U.S. Department of Housing and Urban Development (HUD) from research produced under the Multi-Disciplinary Research Team (MDRT).

This introduction provides some basic policy context for how these important new additions to the positive evidence on federal housing programs fit with other major recent studies. A brief description of the key findings of the articles follows.

The symposium brings together four studies that are the product of an innovative public-private research delivery vehicle created by HUD's Office of Policy Development and Research (PD&R). This vehicle partners academic and research experts with a rapid procurement method, MDRT.

The studies—both on their own and when taken together as larger body of work—provide a valuable addition to the growing body of research on the importance and effectiveness of federal housing programs.

The symposium also includes an international perspective from Kwan Ok Lee of the National University of Singapore. Lee (2018) connects the symposium articles to related research in Asian countries with assisted housing programs, including Singapore, China, and Hong Kong.

Affordable housing advocates have described the need for affordable housing, especially among low-income families and persons, as a national crisis. The latest available HUD estimates show 8.3 million very low-income renter households with "worst case needs" for affordable housing. Watson et al. (2017) found that, although the overall supply of rental stock grew substantially from 2013 and 2015, the supply of stock affordable to very low-income renters actually decreased.[1] The HUD estimates on housing needs are consistent with the findings from major academic institutions.[2]

The articles in this issue bolster the case for the importance and effectiveness of federal rental assistance programs, building on evidence from recent national studies.

HUD recently issued the long-term findings of a landmark study on the effectiveness of different programs in reducing and eliminating homelessness for families with children (Gubits et al., 2016). The **Family Options Study** gathered evidence through the scientific method of random assignment. The study compared the effectiveness of providing HUD rental assistance—Section 8 housing choice vouchers (HCVs)—with alternative approaches including *rapid re-housing* (shorter-term assistance with services), *transitional housing*, and more *usual care* that often includes emergency shelter assistance. The results were dramatic.

Although all four approaches helped families experiencing homelessness, families provided with HCVs had far better and longer-term outcomes than families provided with the shorter-term assistance options. Families receiving HUD rental assistance were far less likely to experience homelessness again, with less than one-half as many episodes of subsequent homelessness as families receiving the shorter-term alternatives. Families provided with HCV rental assistance also had positive outcomes in areas other than their housing situation, including many crucial for child development, such as fewer family-child separations, less psychological distress (usually the mother), less economic stress, less domestic violence, better school mobility, fewer behavior and sleep problems, and less food insecurity (Gubits et al., 2016).[3]

The findings from the Family Options Study built on HUD's previous large-scale evidence-gathering effort in the **Welfare to Work Demonstration Program**. This major demonstration was also based on random assignment. Although the primary goal of the demonstration was to measure outcomes for employment and self-sufficiency goals, it also provided key findings on the effectiveness of HUD rental assistance programs in achieving their core goals of affordability.

The results from the demonstration showed that HCV rental assistance significantly reduced the likelihood of homelessness, overcrowding, and doubling up among all types of low-income families (Mills et al., 2006). Homelessness was nearly eliminated for families offered a voucher. After 4 years of study, 45 percent of families in the control group (not offered vouchers) reported one of the following situations in the past year: homeless at some point, stayed in an emergency shelter, or doubled up with a relative or friend. This prevalence rate was cut to only 9 percent for families

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[1] *Worst case needs* are defined as unassisted very low-income renters who either pay more than one-half their incomes for rent, or live in substandard physical conditions, or both. The estimate of 8.3 million households also does not include other key housing needs—those facing actual homelessness who aren't counted in the Census Bureau data used for the report, or very low-income homeowners who may face similar cost and conditions problems.

[2] See, for example, JCHS (2017).

[3] Note also that shorter-term options, such as rapid re-housing, played an important role and did involve less cost. Longer-term assistance benefits did not add significantly to additional overall costs, however ($3,800 total over 3 years). For additional discussion on the Family Options Study, see HUD PD&R (2016).

who were offered a voucher. In terms of the two groups' reported rates of actual homelessness (on the street or in a shelter), the decrease was from 13 to only 3 percent (a 74-percent drop; Wood, Turnham, and Mills, 2008).[4]

Further recent evidence on the effectiveness of federal rental housing assistance comes from a major and innovative data-matching study: **Childhood Housing and Adult Earnings: A Between-Siblings Analysis of Housing Vouchers and Public Housing**. This landmark effort combined and analyzed long-term, large-scale datasets for millions of households that received HUD housing assistance with U.S. Census Bureau data on household employment, earnings, and other major life outcomes (Andersson et al., 2006; HUD PD&R 2017a).

The study found that children whose families receive HUD rental assistance while the children are teenagers grow up to have higher earnings and lower incarceration rates in their early twenties. Public housing and housing vouchers were both found to have positive and significant effects.

The researchers analyzed the results for different groups (race or ethnicity and gender) and found positive and statistically significant benefits from childhood residence in assisted housing on young adult earnings for nearly all demographic groups. Specific results in terms of long-term earnings from employment found that, for females, each additional year with public housing assistance as a teenager generated a $488 annual increase in earnings as a young adult. The increase in earnings for females with HCV assistance was a roughly similar $468 per year of assistance. For males, the corresponding estimates are $508 (public housing) and $256 (vouchers) per year in additional earnings as a young adult.

Thus, contrary to some speculation or stereotypes, the study found positive effects on later earnings for housing assistance. Both types of affordable housing assistance had positive outcomes relative to not receiving any assistance. Perhaps this finding should not be surprising, as a higher likelihood of such factors as homelessness, housing instability, or reduced family budgets for other necessities would seem likely to have a negative effective on family and life outcomes. Furthermore, the positive outcomes for public housing—including some that were superior to housing vouchers for some groups—are encouraging and may show the need for a variety of affordable housing options and delivery mechanisms.

The study also found additional important positive effects on incarceration rates. Childhood participation in assisted housing was found to reduce the likelihood of incarceration across all household race and ethnicity groups.

This large-scale dataset produced by the Childhood Housing and Adult Earnings study will continue to be a source for additional research findings and thus has the potential to increase its return on federal investment. That is because of a PD&R request, consistent with other HUD-funded

[4] Of the 9 percent of voucher users who experienced housing insecurity, most had left the program willingly or unwillingly due to personal crisis, stints in residential drug treatment or jail, or misunderstandings or noncompliance with program rules.

studies, to make the resulting matched dataset available to other researchers through the U.S. Census Bureau's Center for Administrative Records Research and Applications (CARRA).[5] The privacy and access controls employed by the Census Bureau made such an arrangement possible.

The Census Bureau's own data, through the **Supplemental Poverty Measure** (SPM), provide further evidence for the importance and effectiveness of federal rental assistance programs. Briefly, SPM provides a powerful analytic tool for an alternative means of estimating the magnitude, extent, and character of poverty in America. It measures the rate and the demographics of poverty when other key factors, such as taxes and benefits programs, are taken into account. Under this measure of poverty, housing programs lift more than 3 million people, at least one-third of them children, above the poverty line. Put another way, if federal housing assistance were eliminated altogether, the national poverty rate would increase by a full percentage point, from 15.5 to 16.5 percent (as of 2013) with an even greater increase for children in poverty—a 1.4-percent increase from 16.4 to 17.8 percent (Short, 2014).[6]

PD&R's Multi-Disciplinary Research Team

One way that PD&R has sought to more quickly and cost-effectively add to the body of HUD evidence-based research and to create information on which to improve policies and programs is through MDRT. PD&R developed the MDRT vehicle to assemble a team of qualified researchers that could be on call to deliver sound, objective research on high-impact policy issues. Researchers are selected for their expertise to produce an array of high-quality, short-turnaround research. MDRT researchers use a variety of HUD and external data sources to answer research questions relating to HUD's priority policies and strategic goals.

Reports produced by MDRT are intended to have a high impact. They provide sound, data-based research and analysis to answer highly relevant policy questions in a timely manner and produce results that can be applied in practical ways to federal programs for affordable housing and economic development.[7]

[5] For additional background on CARRA and PD&R's participation and encouragement of its research opportunities, see HUD PD&R (2017b, 2017c). For PD&R's encouragement of the use of CARRA for cooperative agreements issued under the Research Partnerships vehicle, see huduser.gov/portal/oup/research_partnerships.html. For a list of working papers produced through the Census Bureau's Center for Administrative Records Research and Applications, see https://www.census.gov/library/working-papers/series/carra-wp.html.

[6] For percentage increases in poverty rate, see Short (2014: 12), Table 5a. Although the SPM measure includes housing subsidies from federal, state, and local governments, the vast majority of assistance is from the federal government. For additional findings on the effectiveness of housing assistance using the SPM, see GAO (2015). For additional private research findings on the effectiveness of housing assistance, including through use of SPM, see Fischer (2015) and Sherman, Trisi, and Parrott (2013).

[7] Reports from the MDRT are all available in a single location on PD&R's HUDUSER website at huduser.gov/portal/publications/mdrt_reports.html. In addition to MDRT, PD&R implemented another vehicle for relatively rapid research results with a high return on investment of federal taxpayer funds, through cooperative agreements with colleges, universities, and other outside nonprofit research organizations—the Research Partnerships program. For more information, see HUD PD&R (2017d).

Discussion of Symposium Articles

The article by Kirk McClure not only builds on previous research on the length of stay in assisted housing, but adds a critical piece that has been missing in past attempts (largely due to the limited scope and lack of complex methodology in previous attempts). Using MDRT resources, McClure (2018) is able to analyze HUD administrative data over a 20-year period, from 1995 through 2015. He applies a critical survival function analysis that analyzes the proportions of a specific cohort (by year of entry) of assisted households that remain in assisted housing (that is, "survive") after any specified length of stay over a 13-year period.

McClure finds that, although a substantial number of households stay 13 or more years in assisted housing, the typical household in assisted housing stays an average of 6 years. Length of stay also varies by household type. Elderly households stay about 9 years, and nonelderly households with children stay approximately 4 years. The article also finds that the average length of stay in assisted housing has been generally increasing over time for most cohorts of assisted households, influenced by factors such as household characteristics and market conditions.

Casey Dawkins and Jae Sik Jeon examine trends in housing cost burden for HCV households between the years 2003 and 2015. They use HUD administrative data for a cohort analysis of those households that initially leased up in 2003 and 2008. The research aims to identify household, housing, and geographic factors associated with housing cost burden in the HCV program.

Dawkins and Jeon (2018) find that housing cost burdens have risen among HCV households since 2003; the year-to year changes in housing cost burden roughly follow trends in the recent housing market cycle. Housing cost burdens have been particularly high for households with the lowest incomes. Households headed by females, nonelderly persons, non-Hispanic Black persons, and persons without a disability were more likely than other households to exhibit severe housing cost burdens.

Anne Ray, Jeongseob Kim, Diep Nguyen, Jongwon Choi, Kelly McElwain, and Keely Jones Stater address the continuing loss of the assisted housing inventory and raises the question on the long-term sustainability of affordable housing, particularly for families with children. This article updates Econometrica (2006), a study of the risk of loss of affordable housing from HUD's multi-family portfolio between 1998 and 2004. Ray et al. (2018) update the 2006 study by replicating the cross-tabulation and multivariate analyses for HUD's multifamily portfolio, of 18,000 develop-ments and 1.5 million housing units, for 2005 through 2014.

This updated analysis shows a continuing transition from HUD's older mortgage programs toward greater reliance on Section 8 rental assistance to provide affordable units. More owners made active decisions to opt in to Section 8 assistance in the latter period, and HUD reduced enforcement and foreclosure actions. Factors such as for-profit ownership and low rent-to-FMR (Fair Market Rent) ratios continued to be associated with higher risk of affordability loss, but these factors were less influential in 2005-to-2014 than in the original study.

Ray et al. (2018) also assess the stability of housing for elderly residents and persons with dis-abilities, funded by HUD's Section 202 program. They also explore the use of low-income housing tax credits and HUD refinancing to preserve affordability in Section 8 developments. The analysis finds that these preservation tools are associated with extended affordability for thousands of HUD-assisted properties. Additional preservation initiatives and improved targeting may be needed to preserve other HUD-assisted properties, particularly smaller developments in strong real estate markets.

Finally, Sandra Newman and Scott Holupka focus on the quality of assisted housing and find that the government inspection and quality control systems play a role in providing physically adequate housing to assisted housing residents.

The authors use two separate and interesting measures of housing quality developed using data from the 2011 and 2013 American Housing Survey. Both indices indicate that the quality of assisted housing is comparable with that of unassisted housing (Newman and Holupka, 2018). The findings demonstrate that the current inspection and quality control systems appear to achieve the goal of providing physically adequate housing to assisted housing residents. Housing quality varied by the type of assisted housing; for example, disabled households had better housing quality using a voucher compared with living in multifamily housing. For large households, living in the South and living in public housing were associated with considerably worse housing quality.

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Guest Editors

Meena Bavan is a social science analyst in the U.S. Department of Housing and Urban Development, Office of Policy Development and Research.

David Hardiman is a program analyst in the U.S. Department of Housing and Urban Development, Office of Policy Development and Research.

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Length of Stay in Assisted Housing

Kirk McClure
University of Kansas

Abstract

This research addresses the length of time that households remain in the various assisted housing programs administered by the U.S. Department of Housing and Urban Development. The research finds that the typical household in assisted housing now stays for about 6 years, and this figure is increasing for all groups of assisted households. The elderly stay for about 9 years, while nonelderly families with children stay for about 4 years. Racial and ethnic minorities seem to stay for longer in the Housing Choice Voucher program, but the influence of race and ethnicity is less within the public housing and the Section 8 project-based housing programs. Market conditions influence length of stay in assisted housing in a manner suggesting substitution effects. Where the rents on housing in the private marketplace are comparatively high or the availability of rental housing is comparatively low, households in assisted housing tend to stay longer.

Introduction

A household enters an assisted housing program by demonstrating income eligibility, usually after a lengthy waiting period often measured in years (Smith et al., 2015). Once in an assisted housing program, the household may remain indefinitely, but a household may choose to leave assisted housing for any number of reasons. These reasons include change of household needs, eviction for noncompliance with program or landlord rules, loss of income, or graduating out of need as income rises.

To inform budget and policy decisions concerning the various rental assistance programs, the U.S. Department of Housing and Urban Development (HUD) needs accurate and reliable length-of-stay estimates for households in the subsidized housing programs it administers (Thompson, 2007). The objective of this research is to use the HUD administrative data to analyze specific cohorts of assisted households over time to obtain as complete a picture as possible of the influences of actual household experiences on length of stay in assisted housing programs. These programs include the public housing program, the Housing Choice

Voucher (HCV) program, and the Section 8 New Construction/Substantial Rehabilitation project-based housing program.[1] The analysis examines these programs over time with the time spans varying as a function of the available data.

The analysis looks at income level, source of income (for example, income from wages and income from public assistance) and various household characteristics (for example, elderly, disabled, and nonelderly and nondisabled households), as well as housing market conditions (for example, tight versus soft markets) that influence the length of stay of various cohorts of assisted households. In addition to basic length of stay, the analysis replicates and extends the research literature by including survival analysis and other alternative methods that provide a realistic picture of how long households remain in assisted housing.

The research questions addressed are—

1. How long do HUD-assisted households stay in the public housing, HCV, and project-based Section 8 programs (examined separately)?

2. Has length of stay changed over time and for various cohorts of households (from 1995 to the present)?

3. What factors (for example, household composition, income, and housing market conditions) influence length of stay?

4. Does the distribution of stays reflect a threshold that separates households that exit early from households that stay for an extended period?

The analysis employs a survival analysis approach that includes examination of how household characteristics as well as external market factors influence length of stay. Significant program changes such as flat rents, tenant contributions, and market rent levels can affect the average length of stay observed at a given point in time (Olsen et al., 2005). Changing composition in the assisted population can alter the level of turnover because some types of households, such as the elderly, may remain in the program longer than others (Ambrose, 2005; Cortes, Lam, and Fein, 2008; Freeman, 1998). Changes in HUD's data systems and the completeness and quality of reporting from local public housing authorities (PHAs) can affect estimates of length of stay. These issues are examined to the extent that the completeness and quality of reporting from local PHA permits.

Point-in-time length of stay estimates could be affected by changes in the composition of the assisted population or changes in the data collection procedures that do not represent an actual change in the pattern of decisions by households to exit the program. Much of the prior research used a point-in-time methodology to estimate the average lengths of stay for all households in assisted housing programs at the time of the study. The methodology used here examines all assisted household over a very long time period allowing identification of how lengths of stay for various cohorts have changed over time. Point-in-time studies examine average lengths of stay without firm knowledge of when a household will leave assisted housing.

[1] Section 8 project-based housing includes only housing with the voucher attached to the unit. Tenant-based vouchers and Section 8 certificates are included in the HCV program.

The longitudinal approach used here permits estimating the length of stay of all households that entered and exited assisted housing from 2000 to 2015 and even longer in some cases.

The research measures different lengths of stay in the assisted housing programs (public housing, HCV, and Section 8 project-based housing) for each of the types of participating households. The household descriptors found to be influential on length of stay in prior studies include (1) presence and ages of children; (2) race and ethnicity of head of household; (3) elderly and disability status; and (4) income (for example, level or poverty status) and sources (wages, public assistance, and so on).

Where possible, the research generates these estimates over time spans that cover variations in programmatic and market factors that influence lengths of stay. Programmatic factors include (1) changes in data reporting system and (2) PHA participation in Moving To Work (MTW) and other special initiatives.[2]

Housing market factors have also been shown to influence length of stay (Freeman, 2005). These market factors include (1) vacancy rate, population size, and median rents; (2) region of the country; and (3) incidence of poverty.

Prior Research

Several pieces of research have been published addressing the factors that influence the length of stay of a household in assisted housing and the timing of the decision to leave. Most of these studies use HUD administrative data to investigate these issues. Collectively, the research demonstrates that the length of stay in assisted housing varies by program, by household type, and by the housing market conditions in which the household resides.

Hungerford (1996) was the first to venture into explaining variation in the length of time that an assisted household remains in a housing program. He employed a hazard model, which estimates the probability that a household will leave at any given time. He drew his data from the Survey of Income and Program Participation, a household level longitudinal panel study carried out by the U.S. Census Bureau. The results indicated that elderly households and female-headed households tend to remain longer in assisted housing. He found that households with greater educational attainment remain for a shorter period. Households with children also have shorter stays.

Bahchieva and Hosier (2001) examined administrative data from the New York City Housing Authority. The lengths of stay in public housing were found to be very long. Half of all spells lasted 42 years or more, and a quarter lasted 55 years or more. New York City is an exceptionally tight, high-priced housing market, and its public housing developments are generally viewed as high-quality. These factors may contribute to long spells in public housing, which may not be the case in other housing markets. The authors found that shorter lengths of stay in public housing were associated with being young, very old, single, White, non-Latino recent immigrant, nonuser of public assistance, having a higher income, and living in a smaller apartment.

[2] The MTW program permits high-performing PHAs greater flexibility in the administration of their project-based and tenant-based funds so as to test innovative, locally designed strategies to use funds more efficiently. See HUD (2017).

These two studies did not make use of HUD administrative data. With HUD data, the research can cover a much wider study area and can capture specific variations between programs. A variety of research projects have used HUD administrative data for this purpose.

Lubell, Shroder, and Steffen (2003) used data from HUD's Multifamily Tenant Characteristics System (MTCS) and Tenant Rental Assistance Certification System (TRACS). The MTCS data cover public housing and vouchers. The TRACS data cover the Section 8 project-based housing developments as well as a variety of other project-based subsidy programs. The authors focused on both length of stay in assisted housing as well as whether assisted households worked. They found that five of every nine nonelderly nondisabled assisted tenants are employed. They found that the median length of stay was 4.69 years in public housing and 3.08 years in the HCV program. The shortest stays were found among households with children and the longest among elderly households and households with disabilities.

Olsen, Davis, and Carrillo (2005) looked at HUD data from 1995 to 2002 to estimate differences in attrition rates among households in the HCV program, but not the various HUD project-based programs. The authors found that elderly or disabled households are less likely to leave the program and that the prevailing vacancy rate in the market influenced decisions to leave, with greater vacancy rates associated with a lower probability of leaving assisted housing. The authors argued that vacancy rates not only describe market softness but also moving costs leading to ambiguous expectations for this relationship. A significant contribution of their research is the analysis of administrative decisions by PHAs. The authors found that large decreases in the HCV program's payment standard, which sets a ceiling on the maximum amount of subsidy that can be given to any one household, have a very small effect on program attrition. The same is true for increases in the tenant contribution, that is, the share of the income of each household that must be contribute toward payment of rent and utilities.

Ambrose (2005) examined households in both the tenant-based HCV program and the project-based public housing and Section 8 programs. Rather than looking at the length of stay in assisted housing, he employed a hazard rate approach which models the influences upon a household's decision to leave assisted housing at any given point in time. He found that both characteristics of households and housing markets influence that decision. Among the household characteristics, the likelihood of leaving a program increases with the presence of children and with larger households and decreases among households that are elderly or disabled and also decreases among households that are Black or Hispanic. Among employed households, he finds limited support for the idea that increased wages increase the likelihood of leaving public housing but not for the other programs. The same is true with income level generally; higher income households are more likely to leave. He found mixed results on the influence of housing market characteristics. Greater poverty in the neighborhood decreases the probability of leaving assisted housing, but higher educational attainment among the neighborhood population increases the probability of leaving. Finally, the greater the level of housing price appreciation in the market, the lower the level of leaving housing assistance. Ambrose noted the similarities of his findings with Hungerford (1996) a decade earlier.

Cortes, Lam, and Fein (2008) found that the demographic profiles and household composition of assisted tenants changed, and such changes influence the length of stay. Their study particularly focused on how the presence of children influenced length of stay in the HCV program, and they found that the presence of an infant or a toddler increases a household's length of stay in the HCV program. The presence of other children, however, reduced the effect. The presence of teenagers, especially male teenagers, reduced the length of stay.

Climaco et al. (2008) again examined only households in the HCV program, focusing on the use of the portability feature of the program. They examined households that received voucher assistance from 1998 to 2005, finding that 8.9 percent made a portability move. The rate of portability movers was highest among Black households (10.3 percent) compared with White households (8.1 percent) and Hispanic households (8.6 percent). Households with young children or with a younger head of household were more likely to make a portability move than is true for all HCV households. The length of stay in the HCV program is influenced by portability moves as these moves are most likely to occur between the fourth and fifth years of participation. The authors found that HCV households that made portability moves relocated to census tracts with lower poverty rates.

Haley and Gray (2008) looked at just those households in Section 202 supportive housing for the elderly. Their study period was limited to a single year, 2006. They found that residents of Section 202 housing developments had a median stay of 4 years with 18 percent of all households residing in the housing for more than 10 years. Typically, elderly persons admitted to Section 202 projects reside for longer periods of time in this kind of housing than do the elderly households admitted to public housing, other multifamily assisted housing, or using vouchers.

Smith et al. (2015) make an important contribution to the research on length of stay in assisted housing. They used data from the Urban Institute's HOPE VI Panel study to look at what happens to housing assistance leavers. This panel followed 887 households from five housing developments from 2001 to 2005. During that period, 103 households left housing assistance. The authors found that households leave housing assistance for both positive and negative reasons. Positive reasons include marriage or a wage increase; negative reasons include breaking program rules, being evicted, or being relocated. The housing assistance leavers were found to be doing better than those still in public housing or receiving rent subsidies; they had higher incomes, were more likely to be married, and lived in lower poverty, safer communities. Not surprisingly, households that left for negative reasons were found to be worse off than those who left for positive reasons.

The prior research confirms that multiple factors influence that amount of time that a household resides in assisted housing.

These factors include demographic factors such as—

- Age: Elderly households generally stay longer.
- Disability: Households with disabled individuals generally stay longer.
- Children: The presence of children in a household tends to shorten the stay.

- Gender: Female-headed households tend to stay longer.
- Race: Minority households, especially Black households, tend to stay longer but also tend to make greater use of portability moves within the HCV program.
- Income: Higher income is associated with shorter stay.
- Welfare: The lower income with welfare usage is associated with longer stays.
- Education: Higher levels of educational attainment are associated with shorter stays.

These factors also include market conditions such as—

- Vacancy: Researchers disagree on the influence of vacancy rates. Some research suggests that tights markets (low vacancy rates) inhibit moving thus lengthening stays in assisted housing. Other research suggests that soft markets (high vacancy rates) contributed to longer stays.
- Prices: A high level of rent and rent inflation is associated with longer stays.

These factors include administrative decisions within the HCV program such as—

- Payment standards: Decreases in payment standards are not associated with households leaving the program.
- Tenant contribution: Increases in the tenant's contribution toward rent causes greater program attrition.

This information guides the current analysis of length of stay in assisted housing.

Methods and Data

This research assesses the length of stay in assisted housing by households. The research uses methods that calculate the period of assistance for different types of households, in different types of markets, confronting different sets of administrative procedures.

It is important to note at the outset that changes in length of stay vary by household type, by program, and by housing market conditions. All of these variations are examined. The reasons that a household chooses to leave assisted housing are not recorded in the administrative data. Thus, it is not known if a household left because their income rose so that the household graduated out of assisted housing, or if the household had to leave due to noncompliance or breakup of a household. Whatever the cause, variations in the length of stay in assisted housing can be seen across different household groups. The programs are increasingly serving older populations. The lengths of stay in these programs will become longer as elderly households are prone to longer stays. Variations in length of stay can be seen across different housing markets. As rents continue to rise faster than inflation and faster than the incomes of renter households, extremely low-income renter households will have fewer and fewer private market alternatives, preventing them from leaving assisted housing. HUD administrative data were explored to parse out these variations.

Administrative data are not always complete or accurate. As was true with prior research, many household records contain suspect information requiring decisions on treatment of these troublesome data records. Households with missing data, miscoded data, and otherwise suspect data were omitted.

The research examined individual households to assess whether tenant behavior changes over time through a cohort-based method. This method can provide accurate, readily understandable, longitudinal descriptions of the assisted population's lengths of stay in assisted housing. These lengths of stay are analyzed across different points in time, across households of different types, and across different housing markets, all which may affect households' decisions to exit the various public assistance programs.

The household data were drawn from HUD's administrative data. These household level data were merged with American Community Survey data describing demographic, housing, and economic conditions of the markets where the assisted households reside.

The primary database for this study is the recently created Longitudinal Occupancy, Demography, and Income (LODI) file that combines data from MTCS and TRACS for 1995 through 2015. This 21-year timeframe offers the opportunity to better examine any changes over time in the length of stay of households in any of the three major HUD rental assistance programs.

The data were collected from three types of files. For the years 2003 through 2015, the data came from the combined LODI reporting system, which contained data from the three major programs. For the years 1995 through 2002, the data came from two separate systems. The MTCS data cover public housing as well as tenant-based vouchers combined with the earlier Section 8 Certificate program. The TRACS data cover the various Section 8 project-based programs as well as a variety of other multifamily programs. The files were merged to form a single dataset covering all reported households in the following programs—

1. The HCV program: This program includes all voucher households reported by PHAs plus Section 8 Certificates reported in 2002 or earlier but not including households in the MTW program.

2. The public housing program: This program includes all reported public housing households from PHAs that were not in the MTW program.

3. MTW PHAs: This program includes all households reported by MTW PHAs whether the household is using a tenant-based voucher or project-based assistance.

4. Section 8 project-based program: This program includes all households in units assisted by the regular Section 8 New Construction/Substantial Rehabilitation program.

5. Section 202/8: This project-based program serves the very low-income elderly through nonprofit sponsors.

6. Section 202/811 project rental assistance contracts and Section 202/162 project assistance contracts: this group of project-based programs covers housing for the elderly and disabled that received capital advances to nonprofit sponsors.

Note that the following programs were not included in the analysis: (1) the Section 8 Moderate Rehabilitation program, (2) the Rent Supplement program, (3) the Rental Assistance Program, (4) the Section 236 program, and (5) the Below Market Interest Rate program.

Analysis

The data were examined to identify their scale and reliability. Survival functions were generated to illustrate the pace of exits from assisted housing by program and the changes in the functions over time. Next, separate analysis of the length of stay in assisted housing was performed by program for different types of households and for different racial and ethnic groups. Last, the analysis examined the possible drivers of the decision of assisted households to exit assisted housing.

Scale of the Data in the Study

Exhibit 1 describes the scale of the data brought to this study. Over 80 million records were included in the study. Note that this exhibit counts all households that entered, left, or remained

Exhibit 1

Count of Assisted Household and Percent Ending Participation by Program and Year of Reporting

Year of Reporting	Housing Choice Voucher Count[a]	%	Public Housing Count[b]	%	Moving to Work Count[c]	%	Section 8 Project Based Count[d]	%	Section 202/8 Count	%	Section 202/811/162 PRAC Count	%
1995	176,152	13	495,737	10								
1996	238,845	14	480,771	12								
1997	320,084	14	520,614	13								
1998	307,090	9	342,646	10			860,593	9	193,981	7	35,554	8
1999	865,491	11	660,252	13			801,643	10	188,825	8	42,556	7
2000	1,178,121	12	883,790	13			845,762	17	198,221	13	52,230	13
2001	1,090,084	15	659,160	13			915,548	13	203,606	11	61,514	11
2002	1,023,810	15	519,920	19			852,434	14	192,555	12	65,276	11
2003	2,018,606	13	1,067,758	18			1,147,450	16	246,791	14	22,158	14
2004	2,033,948	14	1,131,311	20			1,223,538	18	253,507	15	25,655	15
2005	2,079,755	16	1,159,520	21			1,227,866	18	250,573	15	27,824	16
2006	2,231,601	17	1,277,773	23	4,067	0	1,208,650	18	247,528	15	29,558	16
2007	2,236,668	15	1,274,534	20	56,367	5	1,254,894	19	246,232	15	32,393	16
2008	2,266,021	14	1,290,500	19	106,875	12	1,238,125	19	242,021	15	33,391	16
2009	2,262,709	14	1,266,540	18	148,896	14	1,229,023	18	238,475	15	34,463	16
2010	2,239,551	14	1,282,782	18	208,619	15	1,225,216	18	236,434	15	35,948	15
2011	2,211,323	13	1,315,687	18	270,762	17	1,225,002	17	235,064	14	36,842	15
2012	2,164,736	12	1,280,553	16	248,552	5	1,219,145	18	232,829	15	37,477	16
2013	2,158,019	12	1,285,272	17	256,459	8	1,202,938	18	229,948	15	37,827	16
2014	2,159,297	12	1,328,168	20	354,135	25	1,198,642	17	229,105	15	37,954	15
2015	2,206,597	12	1,318,363	21	389,193	27	1,205,568	18	229,409	15	38,730	15
All years	33,468,508	14	20,841,651	18	2,043,925	16	20,082,037	17	4,095,104	14	687,350	14

[a] *Includes Section 8 tenant-based certificates.*
[b] *Includes only units administered by non-Moving to Work public housing authorities.*
[c] *Includes both project-based and tenant-based units.*
[d] *Does not include Section 202/8 units.*
PRAC = project rental assistance contract.

in each program in each year. Thus, to the extent that a household left, and a new household moved in, a unit can be counted multiple times in a single reporting year. The data are less comprehensive in the early years of the automated MTCS and TRACS data entry systems. Thus, the numbers of households included in the data from 1995 through 1998 are smaller than in the later years, 2003 through 2015, when the data collections systems were up to speed.

Exhibit 1 indicates—

- Data are available and reliable for the public housing program from 1995, although the level of reporting is lower from 1995 through 2002.
- The adoption of the MTW program changed the reporting requirements for the PHAs participating in that program. Thus, from 2006 forward, the MTW public housing and voucher households are reported separately.
- Data are also available for the HCV program from 1995, but the data are considered to be more reliable from 1999 forward.
- Data are available for the Section 8 project-based programs from 1998 forward.

Exhibit 1 lists the percentage of reporting households in each year that ended participation in the housing assistance program. The rates of program exiting do vary from program to program and over the decades of the study period. However, the general finding is that rates of exiting rental assistance do not vary by much. Over the entire study period, the percentage of households that ended participation averaged 14 to 18 percent each year for all programs. Thus, 1 in 5 to 1 in 7 assisted households leave each program in each year.

The programs differ in terms of the rates of exit—

- An average of 14 percent of participating households in the HCV program exit each year. This annual average rate of exit ranged from a low of 9 percent to a high of 17 percent with no clear pattern over the study period.
- Households in the public housing program ranged from 10 percent to 23 percent with an average of 18 percent exiting each year.
- Households in the Section 8 project-based housing developments exited at annual rates from 9 percent to 19 percent with an average of 17 percent.
- The Section 202/8 households and Section 202/811/162 households reported very low rates of exit in the early years of 1998 and 1999. These reports may be unreliable given that they rose very sharply in 2000 and have remained relatively steady since that time. Since 2000, both sets of the Section 202 developments have experienced exit rates ranging from 11 percent to 16 percent per year.

In terms of the percent of assisted households leaving the housing assistance programs in any one year, all programs peaked in the mid-2000s. Exit rates for the HCV program peaked in 2006, public housing peaked in 2006, and Section 8 project-based housing peaked in 2008. The mid-2000s were a period of turmoil in housing markets, but those problems were more keenly felt in the markets of owner-occupied housing and not in rental markets.

Survival Functions

Survival functions indicate the proportion of a selected group of assisted households that remain in assisted housing (that is, "survive") after any specified length of stay. Exhibit 2 presents survival functions for four cohorts of tenants for each of the three major housing assistance programs. The cohorts are based on households that lived in or exited from assisted housing during 4 different years: 2015, 2010, 2005, and 2000. The changes in these functions display the changing trends in the patterns of staying (or surviving) in assisted housing. The charts illustrate survival from program entry through 13 years, although a small proportion of households may stay substantially longer. Survival function illustrations have the advantage that they identify any thresholds beyond which there are either rapid withdrawals from the programs or stabilization of the stays (Thompson, 2007). The charts answer questions such as—

- What is the general shape of the survival function?
- Is there a point where there is rapid exiting from the programs?
- Is there a point where the pace of exiting stabilizes?
- How do the programs compare to each other?

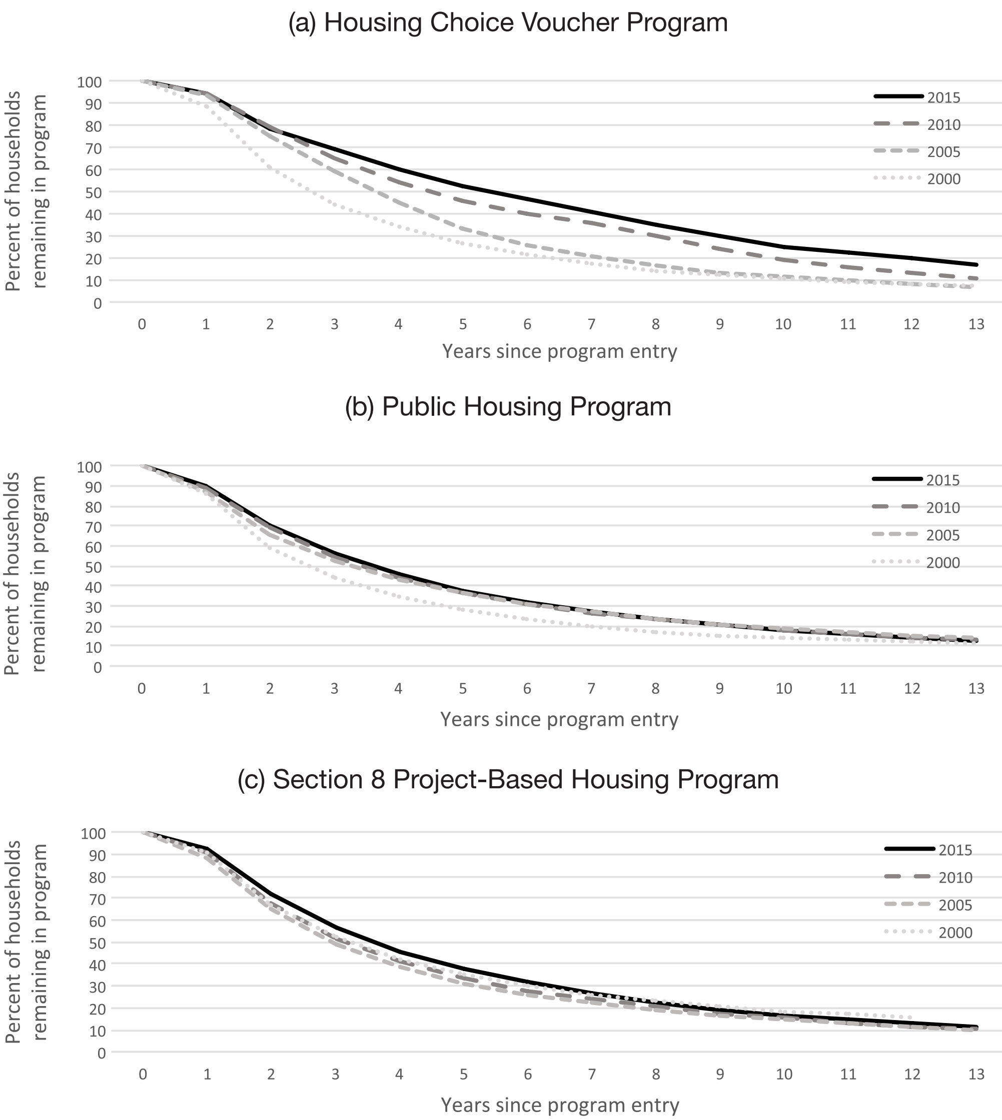
Exhibit 2 illustrates that, typically, 90 percent of households remain in assisted housing through the first year. The losses are minimal during the first year, probably because of a year-long lease on the assisted unit. This has the effect of keeping households in the unit. After the first year, the survival function reflects the successive loss of households from the programs for each length of stay in years. In all cases, the figures illustrate a very standard form of survival function, with survival always decreasing but at a decreasing rate over time.

For the HCV program, the shape of the survival functions has not changed dramatically. However, they have shifted toward a horizontal axis more so than either the public housing program or the Section 8 project-based program, as HCV tenants are choosing to stay longer. Perhaps this shift reflects a response to worsening rental housing market conditions. After the first year, the HCV survival functions do not show any dramatic thresholds where the rates of exits change substantially. There is no point at which the pace of exits stabilizes. Rather, the most recent functions for 2010 and 2015 show a steady loss of households at a gradually slowing pace.

For the public housing and project-based Section 8 programs, the survival functions have changed very little over time. Both programs, in all four periods, show a steady decline in the percentages of assisted households that remain in the program. Neither program shows evidence of any thresholds where the pace of change shifts dramatically or lengths of stay after which the pace of change stabilizes.

Exhibit 2

Survival Functions by Household Cohort and Program Type



Length of Stay by Program

Exhibit 3 indicates the average length of stay of households that exited the various programs by the year of exit. This exhibit provides the means to compare the typical length of stay across the programs and over the entire study period.

Exhibit 3

Average Length of Stay of Households in Assisted Housing by Program by Year of Exit

Year of Exit	Housing Choice Voucher[a]	Public Housing[b]	Moving to Work[c]	Section 8 Project Based[d]	Section 202/8	Section 202/811/162 PRAC	All Programs
1995	0.9	4.6					3.5
1996	1.3	4.8					3.5
1997	1.6	4.6					3.4
1998	1.7	4.2		5.3	6.2	2.0	4.5
1999	2.6	3.9		5.0	6.2	2.2	3.8
2000	3.6	4.3		5.0	6.2	2.5	4.4
2001	3.8	5.0		4.5	6.0	2.6	4.4
2002	3.6	5.3		4.5	6.1	2.8	4.4
2003	3.6	5.1		4.5	6.0	2.4	4.4
2004	4.0	5.7		4.7	6.1	2.5	4.8
2005	4.5	6.0		4.7	6.2	2.6	5.0
2006	4.9	6.8	5.0	4.7	6.2	2.8	5.5
2007	4.9	6.1	5.5	4.7	6.2	2.9	5.3
2008	5.1	5.6	6.2	4.8	6.2	2.9	5.2
2009	5.4	5.5	5.5	4.9	6.3	3.1	5.3
2010	5.8	5.9	6.6	5.0	6.4	3.3	5.6
2011	5.8	5.5	6.2	5.0	6.4	3.4	5.5
2012	5.7	5.4	6.1	5.0	6.5	3.5	5.4
2013	6.0	5.5	5.4	5.1	6.5	3.8	5.6
2014	6.5	5.8	6.2	5.1	6.7	4.1	5.9
2015	6.6	5.9	5.7	5.3	6.7	4.3	6.0
Median 2015	4.8	3.0	4.0	3.0	4.4	2.4	3.6
Average all years	4.9	5.6	5.9	4.9	6.3	3.0	5.1
Median all years	3.1	2.6	4.4	2.6	4.1	1.9	2.9

[a] *Includes Section 8 tenant-based certificates.*
[b] *Includes only units administered by non-Moving to Work public housing authorities.*
[c] *Includes both project-based and tenant-based units.*
[d] *Does not include Section 202/8 units.*
PRAC = project rental assistance contract.

The reliability of the data becomes an issue with the examination of this exhibit. During the early years of HUD's automated tenant data systems, the reporting of household stays may have been biased. Households that lived in assisted housing for a long time prior to the automated systems often did not have had their date of admission recorded. As a result, the households with complete records, including both date of admission and date of exit, may be biased toward those households that entered assisted housing only a short time before the year of exit. Thus, the length of stay figures become more trustworthy after 1998, as the automated systems matured.

With this caveat, it is apparent that the length of stay in assisted housing has grown longer in all programs over the study period. In 2000, the typical household that ended participation in assisted housing lived in that housing for 4.4 years. By 2015, the typical household that ended participation had lived in assisted housing for 6.0 years, an increase of 1.6 years. The increase in average length of stay among households that left assisted housing was greatest in the HCV program, growing by 3.0 years from 3.6 in 2000 to 6.6 in 2015. The increase was smaller in public housing. The average length of stay by households leaving public housing was 4.6 years in 1995, falling slightly to 4.3 years in 2000 but growing to 5.9 years in 2015, an increase of 1.6 years. The Section 8 project-based housing program is more stable in terms of the length of stay than the other programs. The Section 8 program had an average length of stay of 5.0 years in 2000, rising less than one-third of a year to 5.3 years in 2015, after experiencing small increases and decreases in the intervening years.

The MTW PHAs generally followed the same trend, with increasing length of stay over time. Unlike the other programs, households in MTW programs showed a slight drop in average length of stay from 2014 to 2015. Because HUD gives discretion to MTW PHAs to alter their approach to delivering assisted housing and the mixing of tenant-based households with project-based households, this volatility could be expected.

The Section 202/811/162 developments experienced longer than average stays that mirrored the regular Section 8 project-based developments. The special needs households served by Section 202/811 and 202/162 developments had the shortest average length of stay, but they also experienced a large proportional growth in length of stay from 2.5 years in 2000 to 4.3 years in 2015.

Length of Stay by Household Type

Prior research indicates that the length of stay in assisted housing varies with the type of household. Elderly households and households with disabilities tend to stay longer than nonelderly, nondisabled households. Households without children tend to stay longer than households with children.

By 2015, the housing assistance programs helped about 5.1 million households, up from 4.0 million in 2000. HUD categorized these households by three characteristics of household type: (1) elderly or nonelderly, (2) disabled or nondisabled, and (3) with or without children. Exhibit 4 indicates that the largest group is elderly households with no children, at 33 percent of the total. In size, the nonelderly with children group follows at 32 percent of the total. This is a reversal in the rankings of these two categories. In 2000, nonelderly households with children were the largest household type comprising 43 percent of the total. Growth in the population of assisted households is almost entirely among elderly households and households with disabled members. These two groups grew collectively by about 1 million households from 2000 to 2015. Nonelderly households with children grew by fewer than 20,000 households during the same time period.

The message to take from exhibit 4 is that changes in the composition of the assisted households very likely drive changes in the length of stays in assisted housing. Elderly households and households with disabled people are known to remain in assisted housing longer than nonelderly, nondisabled households. This shift toward more elderly and disabled households will generate longer stays in assisted housing independent of changes in other factors.

Exhibit 4

Households in Assisted Housing by Household Type for Years 2000, 2005, 2010, and 2015

Household Category and Subtotals	Year of Reporting							
	2000		2005		2010		2015	
	House-holds	Percent	House-holds	Percent	House-holds	Percent	House-holds	Percent
Household category								
Elderly, no children, nondisabled	1,215,988	30	1,401,791	30	1,560,527	30	1,667,674	33
Nonelderly, no children, disabled	503,972	12	745,588	16	900,883	17	917,370	18
Nonelderly, no children, nondisabled	473,984	12	478,776	10	569,279	11	603,364	12
Elderly, with children, nondisabled	38,030	1	45,512	1	49,934	1	49,953	1
Nonelderly, with children, disabled	73,280	2	237,703	5	276,289	5	259,398	5
Nonelderly, with children, nondisabled	1,742,621	43	1,823,221	39	1,819,037	35	1,630,997	32
All households	4,047,875	100	4,732,591	100	5,175,949	100	5,128,756	100
Household subtotals								
Elderly	1,254,018	31	1,447,303	31	1,610,461	31	1,717,627	33
Nonelderly	2,793,857	69	3,285,288	69	3,565,488	69	3,411,129	67
Disabled	577,252	14	983,291	21	1,177,172	23	1,176,768	23
Able bodied	3,470,623	86	3,749,300	79	3,998,777	77	3,951,988	77
With children	1,853,931	46	2,106,436	45	2,145,260	41	1,940,348	38
No children	2,193,944	54	2,626,155	55	3,030,689	59	3,188,408	62
Elderly or disabled	1,831,270	45	2,430,594	51	2,787,633	54	2,894,395	56
Nonelderly able bodied	2,216,605	55	2,301,997	49	2,388,316	46	2,234,361	44

Exhibit 5 examines average length of stay of different households by year of exit from assisted housing, combining all households from all programs. The exhibit is organized by a household type designation used by HUD. This household type designation divides all assisted households into six categories based upon three variables indicating if the household is (1) elderly or nonelderly, (2) disabled or nondisabled, and (3) membered with children or not.

Exhibit 5 presents lengths of stay of households existing from 1995 through 2015 for these household types, extending the period of time studied over the prior research with the caveat that some of the counts are quite small in the early years of 1995 to 2000 for some programs. Despite the longer study period, the results are generally similar to previous studies. Elderly households tend to have longer stays at 8 to 9 years compared to less than 5 years for nonelderly households. Households with children, which often consist of single mothers with children, tend to have shorter lengths of stay. The group of assisted households that has expanded in size the most in recent years is households with disabled members. This group tends to have lengths of stay comparable to those of the nonelderly, well short of the stays of the elderly households.

Exhibit 5

Average Length of Stay of Households in Assisted Housing by Household Type by Year of Exit

Year of Exit	Elderly Nondisabled No Children	Nonelderly Disabled No Children	Nonelderly Nondisabled No Children	Elderly Nondisabled With Children	Nonelderly Disabled WIth Children	Nonelderly Nondisabled WIth Children
1995	7.4	2.9	2.4	6.3	2.3	1.9
1996	7.9	2.3	2.9	6.7	2.0	2.0
1997	7.8	2.4	2.9	7.4	2.5	2.1
1998	7.7	3.0	3.0	8.0	3.4	3.0
1999	7.3	2.8	2.8	7.2	3.1	2.7
2000	7.6	3.4	3.8	8.1	3.7	3.1
2001	7.6	3.5	3.8	7.6	3.5	3.0
2002	7.7	3.6	3.7	8.0	3.6	3.1
2003	7.8	3.6	3.7	8.2	3.6	3.0
2004	8.3	3.9	4.2	9.5	3.8	3.3
2005	8.6	4.2	4.6	10.2	4.2	3.5
2006	9.1	4.7	5.3	12.5	4.7	3.9
2007	8.7	4.5	4.9	10.2	4.4	3.7
2008	8.5	4.5	4.8	9.6	4.4	3.6
2009	8.4	4.6	4.8	9.2	4.5	3.7
2010	8.7	4.8	5.3	9.5	4.9	3.8
2011	8.7	4.8	4.9	9.0	4.9	3.8
2012	8.6	4.7	4.8	8.8	4.5	3.7
2013	8.8	4.9	5.1	9.1	4.6	3.9
2014	9.1	5.0	5.4	9.4	4.9	4.1
2015	9.1	5.1	5.5	9.5	4.9	4.2
Median 2015	6.7	3.1	2.7	6.5	3.3	2.8
All years	8.5	4.4	4.5	9.5	4.4	3.5
Median all years	5.9	2.5	2.0	5.9	2.8	2.2
Growth in years 2000 to 2015	1.5	1.7	1.7	1.4	1.2	1.1

All six household types listed in exhibit 5 experienced longer stays in assisted housing over the study period. With only a few very small exceptions, each household type's average length of stay increased with the passage of each year. However, changes from one year to the next were not dramatic, and the increases were incremental but unequal. The rank ordering of the household types by average length of stay in the late 1990s remained the same in 2015, with elderly households staying longest and the nonelderly with children staying the shortest. However, the amount of growth was only slightly different. The average length of stay for elderly households grew 1.4 to 1.5 years from 2000 to 2015. The stays for the nondisabled, nonelderly households grew by 1.1 to 1.7 years, and the stays for households with disabilities grew 1.2 to 1.7 years.

Average length of stays can be misleading because survival functions of many shapes can have the same average. To prevent being misled by this issue but to make the analysis manageable, exhibits 6 through 11 follow the procedures used by Cortes, Lam, and Fein (2008). These authors examined length of stay of cohorts at three points along the survival function: the 25th, the 50th (median), and the 75th percentile for each of the three major programs. This technique discloses any dramatic shifts in the survival functions, such as a large increase or decrease in the length of stay. Any shift in the survival function will be identified as a significant change in the average length of stay at any one or all of the percentiles.

Exhibit 2 shows that survival functions shifted for households in the HCV program with longer stays in more recent years. Exhibit 6 helps to identify the patterns of change by household type for the HCV program, providing insights into which household types experienced the greatest shifts and in what direction. The simple answer to this issue is that all household types experienced some level of increased length of stay over time. All household types, at all three percentiles, experienced increases in the length of stay during all three periods from 2000 to 2005, 2005 to 2010, and 2010 to 2015. The scales of the shifts were generally comparable. The 50th percentile, or median length of stay, increased from 0.5 years to 3.3 years over the various time periods, with most increasing at the lower end of this range, from 0.5 to 1.1 years, over any 5-year period. The largest 5-year increases in median stays were for elderly households with increases at the median of over 2 years for elderly households with no children and over 3 years for elderly households with children. There was only one exception to the pattern of growth in length of stay for the HCV households; the nondisabled elderly households with children experienced a slight reduction in the median length of stay from 2010 to 2015. It is worth noting that this cohort had one of the longest lengths of stay among all the assisted households at more than 7 years at the median. Thus, a slight downward shift is unremarkable for this already long-tenured population.

The survival functions for the public housing households and the Section 8 project-based households did not shift by much. Thus, the value of exhibits 7 and 8 is to determine whether

Exhibit 6

Length of Stay of Households in the Housing Choice Voucher Program by Household Type for Year of Exit

Year of Exit	Per-centile	Elderly Nondisabled No Children	Nonelderly Disabled No Children	Nonelderly Nondisabled No Children	Elderly Nondisabled With Children	Nonelderly Disabled WIth Children	Nonelderly Nondisabled WIth Children
2000	25th	1.7	0.9	0.9	1.3	0.9	0.9
	50th	4.6	1.8	2.1	3.3	2.0	1.9
	75th	10.3	4.2	5.7	8.2	4.6	4.0
2005	25th	2.6	1.4	1.2	2.3	1.5	1.3
	50th	5.1	2.9	2.8	4.4	2.9	2.7
	75th	10.4	5.3	6.0	8.5	5.0	4.6
2010	25th	3.1	1.7	1.4	3.4	1.9	1.6
	50th	7.2	3.9	3.9	7.7	3.9	3.3
	75th	11.8	8.2	8.9	12.1	8.0	7.0
2015	25th	3.6	1.7	1.4	3.4	1.9	1.8
	50th	8.0	4.2	4.3	7.3	4.4	4.1
	75th	13.7	8.8	10.2	13.1	8.3	7.8

Exhibit 7

Length of Stay of Households in the Public Housing Program by Household Type by Year of Exit

Year of Exit	Per-centile	Elderly Nondisabled No Children	Nonelderly Disabled No Children	Nonelderly Nondisabled No Children	Elderly Nondisabled With Children	Nonelderly Disabled WIth Children	Nonelderly Nondisabled WIth Children
2000	25th	2.1	0.6	0.5	1.5	0.8	0.7
	50th	5.8	1.7	1.2	4.8	1.8	1.6
	75th	12.9	4.0	3.4	16.9	4.4	3.5
2005	25th	2.9	0.9	0.7	3.0	0.9	0.9
	50th	7.3	2.3	2.0	9.5	2.4	2.0
	75th	15.9	5.3	5.7	25.8	5.5	4.3
2010	25th	2.9	1.0	0.9	2.4	1.1	0.9
	50th	7.1	2.5	2.1	6.3	2.4	2.0
	75th	14.6	5.6	5.8	16.6	5.3	4.1
2015	25th	3.0	1.1	0.9	2.4	1.1	1.0
	50th	7.6	2.7	2.4	6.5	2.5	2.3
	75th	15.6	6.1	6.5	15.4	5.4	4.7

Exhibit 8

Length of Stay of Households in the Section 8 Project-Based Housing Program by Household Type by Year of Exit

Year of Exit	Per-centile	Elderly Nondisabled No Children	Nonelderly Disabled No Children	Nonelderly Nondisabled No Children	Elderly Nondisabled With Children	Nonelderly Disabled WIth Children	Nonelderly Nondisabled WIth Children
2000	25th	2.4	1.0	0.7	2.4	1.0	0.9
	50th	6.2	2.2	1.8	6.1	2.2	1.9
	75th	13.1	5.4	4.8	15.0	5.4	4.1
2005	25th	2.3	0.9	0.7	1.8	1.0	0.9
	50th	6.0	2.1	1.6	4.5	2.1	1.9
	75th	12.7	4.7	3.6	12.1	4.7	3.7
2010	25th	2.4	0.9	0.8	2.0	1.1	0.9
	50th	6.1	2.2	1.8	5.4	2.3	1.9
	75th	12.4	4.9	4.5	12.8	4.7	3.8
2015	25th	2.6	1.1	0.9	2.2	1.1	1.0
	50th	6.5	2.6	2.0	5.4	2.7	2.3
	75th	13.1	5.7	4.9	12.0	5.8	4.5

the lengths of stay among exiting household remained stable for all household types. It is possible that the stable overall survival functions masked significant shifts in different directions between household types that washed out when combined. The message from these two tables is that both public housing and Section 8 project-based housing experienced, with only minor exceptions, very small shifts in lengths of stay across all household types across all time periods.

The shifts from one time period to the next in lengths of stay were nearly all small fractions of a year. The same is true for shifts at the 25th and 75th percentiles. The only exception to this shift of any scale is the population of elderly households that are caring for children. This population is largely the caretakers for their grandchildren because the children's parents were no longer able to care for them leaving the elderly to care for grandchildren (Pebley and Rudkin, 1999). This particular cohort experienced some volatility, both up and down, in terms of length of stay. It is important to realize this cohort has the longest length of stay at the upper reaches of the survival function in all three of the major programs. The 75th percentile length of stay is 12 to 15 years, compared with 4 to 10 years for the nonelderly cohorts.

Length of Stay by Race and Ethnicity

Exhibits 9 through 11 perform the same analysis of shifts in survival functions across the rental assistance programs, but with these tables the comparison is across racial and ethnic groups. These tables look for significant shifts in the survival functions for various racially or ethnically defined groups of households across the three rental assistance programs. To keep the tables of a manageable scale, all households have been placed into one of four racial or ethnic groups based on the race and ethnicity of the head of household. The first three groups are households that are non-Hispanic, with separate groups for White, Black, and other non-Hispanic households. The fourth group contains all Hispanics households of any race.

Exhibit 9 lists the lengths of stay along the survival functions for HCV households. All households increased their median lengths of stay over all time periods, but the increases were all small, ranging from 0.5 to 1.5 years. In all cases, the length of stay at the median was greater for minority households compared to White households. Comparing the 2015 with the 2000 cohort of exiters, median stays increased more for Black and Hispanic households than for White and other non-Hispanic households. Over the longer timespan, the 75th percentile length of stay increased substantially among exiters for all demographic groups.

The lengths of stay used for this analysis provide limited information about factors that could lead to disparities in length of stay. Studies by DeLuca, Garboden, and Rosenblatt (2013) and

Exhibit 9

Length of Stay of Households in the Housing Choice Voucher Program by Household Race and Ethnicity for Year of Exit 2000, 2005, 2010, and 2015

Year of Exit	Percentile	White Non-Hispanic	Black Non-Hispanic	Other Non-Hispanic	Hispanic
2000	25th	0.9	1.1	1.0	1.0
	50th	1.8	2.5	2.5	2.3
	75th	4.3	5.1	5.9	5.7
2005	25th	1.3	1.9	1.9	1.8
	50th	2.8	3.5	3.5	3.4
	75th	5.0	6.1	6.1	6.3
2010	25th	1.5	2.1	2.0	2.0
	50th	3.3	4.9	4.4	4.9
	75th	7.4	8.9	8.5	9.1
2015	25th	1.4	2.4	1.8	2.3
	50th	3.9	5.6	5.2	5.8
	75th	8.7	10.2	10.5	10.9

Krysan and Bader (2007) that examined panels of voucher households in individual cities found that minority households confront greater challenges in their search for rental housing. These challenges may influence the perceived desirability of integrated neighborhoods. Discrimination has been found to increase the difficulty of minority households with a voucher (Basolo and Nguyen, 2010).

Both overall increases in length of stay for all demographic groups as well as differences for minority HCV households could be driven by the shrinking availability of units with rents below the Fair Market Rent levels that govern the program. HUD's Worst Case Housing Needs study for 2015 (Watson et al., 2017) and the Affordable Housing Needs study for 2005 (HUD PD&R, 2007) indicate that the availability of rental units below the Fair Market Rent levels fell by about 6 percent over the period from 2005 to 2015. The number of affordable units per 100 income-eligible households fell from 86.6 in 2005 to 81.6 in 2015. If reductions in affordable units were greater in minority-dominated rental markets, it could increase market pressure causing minority HCV households to stay longer in the assisted housing program.

Exhibit 10 finds very small differences between non-Hispanic White households and the three minority groups in terms of increases in median lengths of stay in public housing. This is very different than the increases in lengths of stay in the HCV program, in which all minority groups increased their lengths of stay relative to White households.

Exhibit 11 extends the comparison to the Section 8 project-based housing program. The results are very similar to those for the public housing program. Changes in lengths of stay are generally small from one time period to the next, and the changes contain a mix of both positive changes (longer stays) and negative changes (shorter stays).

Further research using household level survey data is needed to explore the many possible reasons behind the longer lengths of stay in assisted housing among minority households.

Exhibit 10

Length of Stay of Households in the Public Housing Program by Household Race and Ethnicity for Year of Exit 2000, 2005, 2010, and 2015

Year of Exit	Percentile	White Non-Hispanic	Black Non-Hispanic	Other Non-Hispanic	Hispanic
2000	25th	0.6	1.0	0.8	0.8
	50th	1.6	2.3	2.3	2.1
	75th	4.4	5.6	5.9	5.4
2005	25th	0.8	1.3	1.1	1.5
	50th	2.1	3.1	2.9	4.1
	75th	5.5	7.4	7.5	10.3
2010	25th	0.9	1.4	1.4	1.5
	50th	2.3	3.1	3.3	3.6
	75th	5.7	7.1	8.1	9.0
2015	25th	0.9	1.4	1.2	1.7
	50th	2.4	3.2	3.3	4.3
	75th	6.0	7.1	8.0	10.3

Exhibit 11

Length of Stay of Households in the Section 8 Project-Based Housing Program by Household Race and Ethnicity for Year of Exit 2000, 2005, 2010, and 2015

Year of Exit	Percentile	White Non-Hispanic	Black Non-Hispanic	Other Non-Hispanic	Hispanic
2000	25th	1.0	1.2	1.2	1.1
	50th	2.5	2.9	3.1	2.9
	75th	7.1	6.5	7.2	7.1
2005	25th	0.5	1.3	–	1.4
	50th	0.8	1.8	–	2.0
	75th	3.7	5.1	–	10.5
2010	25th	1.0	1.2	1.0	1.2
	50th	2.5	2.7	2.6	2.7
	75th	6.4	5.7	7.3	6.5
2015	25th	1.1	1.4	1.2	1.4
	50th	2.8	3.0	3.0	3.4
	75th	7.0	6.3	7.6	7.5

Note: Insufficient data are available for non-Hispanic other race households in 2005.

Drivers of Length of Stay

Having looked at household the characteristics of race, ethnicity, age, disability and the presence of children, the analysis now turns to identification of what factors, if any, may drive the decision to exit assisted housing. These drivers may include household income level, its source, as well as market conditions, such as vacancy rates and rent levels. The analysis examines individually the relationship between these factors and lengths of stay in assisted housing to establish expectations on the scale and direction of the relationships.

Length of Stay by Income Level and Source of Income

Differences in lengths of stay and changes in lengths of stay from one time period to the next could result from household factors other than race or ethnicity. Households differ by income levels and the sources of that income, both of which could influence decisions to remain in assisted housing or leave to enter the unsubsidized market. Exhibit 12 addresses this issue.

All households in the HCV, public housing, and Section 8 project-based programs benefit from very similar subsidy calculations. For public housing and project-based Section 8, each household generally pays about 30 percent of their adjusted gross income toward the gross rent on the rental unit in which the household lives.[3] In the HCV program, the maximum subsidy provided is tied to a percentage of the local Fair Market Rent, with tenants allowed to pay more than 30 percent of their income for units renting above that level. The program does permit a household to pay up to 40 percent of income on housing if the household chooses to consume more housing.[4]

[3] There are some exceptions from this rule. In some settings, households can be subject to flat rents that can alter the tenant's required contribution as a percentage of income.

[4] McClure (2005) found that, in 2002, 62 percent of HCV households paid 31 percent of income toward rent. Another 21 percent spent more than 31 percent but not more than 40 percent of income. About 17 percent of HCV households spent more than 40 percent of income on rent, a housing cost hardship that the HCV program was designed to prevent.

Exhibit 12

Correlation Between Length of Stay and Income by Source All Programs, 2015

Income Source	Number of Households	Mean Value ($)	Correlation Coefficient	Significance
Total income	454,677	13,747	0.124	**
Adjusted total income	454,677	12,690	0.126	**
Total wage income	163,824	19,598	0.225	**
Total welfare income	109,544	4,016	– 0.120	**
Length of stay		5.2 years		

** $p < .01$.

The rental assistance programs pay the difference between the tenant's contribution and the rent charged for the unit. All participating households are subject to similar eligibility rules limiting their participation in any of the programs. Thus, nearly all households in the programs have extremely low income, generally placing them below 30 percent of the Area Median Family Income of the metropolitan area or the nonmetropolitan county where they live. In 2015, the average household income for the assisted households was between $13,000 and $14,000. This means that the typical household receiving housing assistance lives below poverty. For that year, the U.S. Department of Health and Human Services (2017) set the poverty guidelines at about $12,000 for a family of one, $16,000 for a family of two, and $20,000 for a family of three.

The 2015 households that lived in assisted housing through the HCV, public housing, or Section 8 project-based programs had a mean income of only $13,456. The 2015 households that left assisted housing had a comparable mean income at $13,747. Thus, in terms of income, the households that exited assisted housing were approximately the same as the larger population of households that remained in assisted housing. Higher or lower income does not seem to influence the decision to remain in assisted housing or to exit. About 36 percent of the households exiting assisted housing had income from employment. Not surprisingly, these employed households had higher incomes than their unemployed counterparts at $21,200 with $19,598 of that income from wages. A smaller portion of the 2015 exiting households, 24 percent, had income from public assistance. The income from public assistance is much lower for these households, at only $4,016, bringing them to a total income that averaged only $11,114. Interestingly, about one-third of these public assistance recipient households also had income from employment and that employment income was much larger, at $16,856, than the income from public assistance.

Consistent with the research literature, it was expected that household income for households in assisted housing would be negatively correlated with length of stay. Those with the least income would have been more inclined to remain in assisted housing longer. Those with the greatest income would have a higher capacity to navigate the private, unsubsidized housing market and thus be more likely to end their time in assisted housing. Similarly, it was expected that source of income would matter. If a household had income from employment, it would seem more likely that this household could gain the extra income needed to enter the private market. Thus, income from wages was expected to be negatively correlated with length of stay. Finally, income from the various public assistance programs was expected to create the opposite effect. Income from assistance programs was expected to be positively associated with length of stay as greater public assistance usage would be associated with greater dependency on rental assistance to meet housing needs.

None of these expectations were supported (see exhibit 12). The correlations are all statistically significant at better than the .01 level. However, statistical significance is not policy-relevant significance. The scale of the dataset for this analysis is very large, with hundreds of thousands of households in the three major rental assistance programs in 2015. Almost any analysis generating statistics from a dataset this large will produce statistically significant results. While being statistically significant, the correlation coefficients are small with absolute values ranging from .12 to .22. Coefficients of this scale indicate that the variables explain only about 1.4 to 4.8 percent of the variation in the dependent variable—length of stay. At the very minimum, other factors must explain much more of the variation.

It remains something of an unanswered question why greater income among the eligible poor in assisted housing would be associated with longer stays in that housing rather than shorter stays, and greater public assistance usage would be associated with shorter stays. While perhaps counter-intuitive at first, it may be that families receiving income from job earnings are less resilient, for instance more at risk to loss of that income due to short-term emergencies (for example, becoming sick while in a low-wage job without paid sick leave), or having to move more frequently in order to find alternative employment (DeLuca, Garboden, and Rosenblatt, 2013).

Length of Stay by Rent Levels

Differences in length of stay and changes in length of stay could result from rent levels either charged to the households through the rental assistance program or from the market within which the household lives.

All of the households in the HCV, public housing, and Section 8 programs pay about 30 percent of income on housing. As a result, the burden of rent on the income of the eligible poor is roughly the same across all households. With this equivalent burden, it would be expected that higher or lower rents paid by the tenants would have no effect on length of stay other than the fact that the tenant rent reflects the incomes of the households. Exhibit 11 indicates that tenant income is weakly but positively associated with length of stay. Exhibit 13 suggests that the same holds true for tenant rent at almost exactly the same strength of correlation. In this regard, it can be speculated that tenant rent may not be related to length of stay except through the income effect.

Some households in public housing are subject to flat rents. The expectation was that flat rents, especially if set at a high level, might create pressure on households to leave public housing and enter the private market. This expectation suggests a negative and significant correlation with length of stay, but the opposite was found. There is a significant but small positive relationship between flat rent amount and length of stay for public housing households that are subject to flat rents.

Exhibit 13

Correlation Between Length of Stay and Program Rents All Programs, 2015

Income Source	Number of Households	Mean Value ($)	Correlation Coefficient	Significance
Tenant rent amount	429,215	327	0.123	**
Flat rent amount[a]	62,774	538	0.130	**
Gross rent amount[b]	300,495	854	0.244	**
Length of stay		5.2 years		

** $p < .01$.
[a] *Public housing only.*
[b] *Housing Choice Voucher program and Section 8 only.*

Gross rents are limited in the HCV and Section 8 project-based housing programs. They are limited through the Fair Market Rents published by HUD and, for the HCV program, the payment standards associated with the Fair Market Rents. These Fair Market Rents vary considerably across the county reflecting the rents found in each individual marketplace. However, the great benefit of a household receiving housing assistance through the Section 8 program is that their housing cost burden is the generally the same, 30 percent of income, independent of the surrounding housing market conditions. Given the immunity from market pressures, it would be expected that there would be no correlation between gross rents and length of stay, but the relationship is positive, statistically significant, but small. Such a relationship could be a response to a market substitution effect. If the surrounding market has higher rents, they would be expected to discourage household from leaving assisted housing and moving into the private marketplace which would generate a positive correlation between gross rents and length of stay.

Length of Stay by Housing Market Conditions

The softness of the surrounding rental housing market may influence the probability that a household stays in or exits out of assisted housing. If the household has many options, especially affordable options, then it seems likely that the pace of exiting assisted housing would increase. To determine if this is the case, the households that exited assisted housing in 2015 were examined for correlations between their length of stay and measures of housing market conditions both in the immediate census tract and, if the household resided within a Core Based Statistical Area (CBSA), in the surrounding CBSA. These correlations test whether or not the length of stay is shorter for households living in census tracts with higher rental housing vacancy rates. A second test is whether or not the length of stay is shorter for households living in census tracts with lower gross rent levels. Exhibit 14 examines these issues.

At both the tract and the CBSA level, length of stay is positively associated with population. Locations with larger populations tend to correlate with households staying longer in assisted housing. The incidence of poverty is found to have an inverse effect; the greater the level of poverty in the surrounding tract and CBSA, the shorter the length of stay, suggesting that assisted households are more willing to leave assisted housing if they are subjected to living in a

Exhibit 14

Correlation Between Length of Stay and Program Rents All Programs, 2015

Population	Number of Households	Mean Value	Correlation Coefficient	Significance
Length of stay	430,768	5.94		
Tract population	422,650	4,456	0.05	**
Tract percent poverty	422,640	27.68	– 0.03	**
Tract percent minority	422,640	46.39	0.15	**
Tract median gross rent	422,640	732	0.21	**
Tract rental vacancy rate	422,640	8.14	– 0.08	**
CBSA population	381,009	2,618,041	0.30	**
CBSA percent below poverty	381,009	16.18	– 0.11	**
CBSA percent minority	381,009	32.67	0.19	**
CBSA median gross rent	381,009	858	0.31	**
CBSA rental vacany rate	381,009	8.12	– 0.14	**

** $p < .01$.
CBSA = Core Based Statstical Area.

high-poverty setting. The incidence of the share of racial or ethnic minorities in the surrounding populations is found to have the opposite effect; the greater the incidence of minorities in the population, the longer the stay in assisted housing.

The price of housing and the availability of alternative rental housing in the marketplace are expected to influence the assisted household's decision to stay in or leave assisted housing. Both price and availability effects were found to exist. Length of stay is positively associated with rent levels, again at both the tract and CBSA levels, as would be expected. If the assisted household confronts higher rents in the surrounding neighborhood and the surrounding metropolitan area, it is more likely that the household will remain in assisted housing. Length of stay is negatively associated with rental vacancy rates at both the tract and CBSA levels, as would be expected. If the assisted household confronts tighter rental housing markets offering fewer alternative units for rent, it is more likely that the household will remain in assisted housing. None of the correlations coefficients are compellingly strong. The strongest are the coefficients for median gross rents in the tracts and the CBSAs; these are .26 and .30 respectively. Coefficients at this level explain only 7 percent and 9 percent of the total variation length of stay, leaving the vast majority of the variation to be explained by other factors.

Conclusion

HUD plays a very large role in helping extremely low-income renter households afford the cost of housing. HUD supports housing developments typically occupied by extremely low-income households through the public housing program as well as the Section 8 project-based housing program. HUD also funds the HCV program, which supports extremely low-income households that enter the private marketplace to rent a unit. Once a household begins to receive assistance through one of these three programs, how long will the household stay in the program?

This research finds that the typical household that left assisted housing recently stayed for about 6 years. Differences between types of households are stark; elderly households stayed longer at 9 years, and disabled households stayed for about 5 years, while nonelderly families with children stayed for about 4 years.

The length of stay has increased somewhat over time for all groups. The average length of stay in assisted housing grew for elderly households by 1.5 to 1.7 years from 2000 to 2015. Households with disabilities saw their average stay grow by 1.2 to 1.7 years during the same period. Nonelderly families with children experienced the smallest change; their average length of stay grew by 1.1 years.

Racial and ethnic minorities seem to stay for longer periods of time within the HCV program, but the influence of race and ethnicity is less within the public housing and the Section 8 project-based housing programs.

Among the eligible renter households, all of whom have very low incomes, those with more income seem to stay longer in assisted housing as do those with income from wages. Those households with income from public assistance seem to stay for shorter periods.

Market conditions influence length of stay in assisted housing in a manner suggesting substitution effects. Where the rents on housing in the private marketplace are comparatively high or the availability of rental housing is comparatively low, households in assisted housing stay longer. Where alternative housing is the private market is expensive and scarce, households will stay longer in assisted housing.

The research finds that households that remain in assisted housing tend to follow a common pattern of stays. Once admitted into one of the assisted housing programs, over 90 percent of all assisted household remain in that housing through the first year. From 70 to 80 percent of households remain through the second year. The pace of leaving assisted housing continues but at a decreasing rate over time. About one-half of all assisted households leave by 4 to 6 years after entry, and about 80 percent leave by years 9 to 11.

It is not surprising that the length of stay in assisted housing is increasing. Prior research suggests that this pattern has been seen in the recent past (Ambrose, 2005) as well as the more distant past (Hungerford, 1996).

The prior research, as well as the research presented here, cannot identify definitive reasons for the changes in lengths of stay in assisted housing. The research can only identify relationships that exist between lengths of stay and various forces that might influence a household's decision to leave or remain in assisted housing. The prior research, as well as this research project, confirms that length of stay is related to the household's age, presence of children as well as the ability of the household to find alternative housing in the private marketplace.

While definitive causation is beyond the scope of this study, it is likely that fundamental market forces including increasing housing costs and inadequate incomes play the greatest role. The economic forces in the U.S. rental markets are moving in a manner that probably contributed to the longer stays in assisted housing. From 2000 to 2015, the United States saw median gross rent grow by 54 percent (U.S. Census Bureau, 2017). This growth in rents outpaced inflation by 16 percentage points as the Consumer Price Index grew by 38 percent during the same time period (U.S. Department of Labor, 2017). The rapid growth in rents contributes to the loss of affordable housing in the nation because the incomes of renters are not keeping up with inflation, much less with the growth of rents. From 2000 to 2015, median renter incomes grew by only 31 percent (U.S. Census Bureau, 2017). This trend has continued for a very long time. Despite the rise and fall of prices of homes for owner-occupancy during the housing bubble, its collapse, and the recovery that followed, rents have been on a steady upward path, outpacing both inflation and renter income. As long as this pattern continues, it can be expected that the lengths of stay in assisted housing will continue to increase.

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Author

Kirk McClure is a professor in the Urban Planning Program, University of Kansas in Lawrence, Kansas.

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Housing Cost Burden in the Housing Choice Voucher Program: The Impact of HUD Program Rules

Casey Dawkins
Jae Sik Jeon
University of Maryland

Abstract

U.S. renters' housing cost burdens have reached historic highs, and these burdens fall most heavily on renters earning the lowest incomes. The Housing Choice Voucher (HCV) program, the nation's largest tenant-based rental assistance program, is designed to alleviate high housing cost burdens for qualifying low-income households. In theory, voucher recipients should not spend more than 40 percent of their income on rent while participating in the program, yet research finds that many HCV program participants still experience housing cost burdens in excess of this threshold.

This article examines recent trends and determinants of housing cost burdens for voucher recipients. We rely on cross-sectional and longitudinal data constructed from U.S. Department of Housing and Urban Development administrative files to characterize the prevalence of housing cost burden over the 2003-to-2015 period, explore longitudinal trajectories of voucher recipients who initially leased a unit in 2003, and examine the marginal impact of various factors on the odds of an HCV household experiencing a housing cost burden in 2015. The findings suggest that certain provisions of the HCV program, particularly local payment standards and the restriction on housing cost burden monitoring to those recently admitted or recently moved, play an important role in shaping housing cost burdens.

Introduction

U.S. renters' housing cost burdens have reached historic highs. According to JCHS (2017), the number of renters spending more than 30 percent of their income on rent rose from 14.8 million to 21.3 million between 2001 and 2014, and the number of renters spending more than 50 percent of their income on rent rose from 7.5 million to a record high of 11.4 million. According to the U.S. Department of Housing and Urban Development's (HUD's) *2017 Worst Case Housing Needs* report, these high housing cost burdens fall most heavily on renters earning the lowest incomes. Of those earning less than 30 percent of the Area Median Income (AMI), 65 percent are severely cost burdened, spending more than 50 percent of their income on rent (Watson et al., 2017: table A-1A). These high housing cost burdens reduce income available to meet other important household needs. For example, JCHS (2017) found that severely cost burdened low-income households spend 53 percent less on food, healthcare, and transportation than similar households without housing cost burdens.

The Housing Choice Voucher (HCV) program, the nation's largest tenant-based rental assistance program, is designed to alleviate these high housing cost burdens for qualifying low-income households, while also expanding housing choices in a wider variety of neighborhoods that offer beneficial economic and social opportunities. Rather than limit households to government-owned or subsidized housing options, the HCV program expands the range of potential housing options to include all privately owned rental housing units that are managed by landlords willing to participate in the program. Also, because the HCV subsidy moves with the tenant, the program allows households to flexibly adjust their housing in response to changing household needs and preferences.

Eligibility for the HCV program is limited to low-income renters whose income is less than or equal to 50 percent of AMI, and local public housing agencies (PHAs) are required to allocate at least 75 percent of vouchers to those earning no more than 30 percent of the AMI. For those participating in the HCV program, HUD awards Housing Assistance Payments (HAPs) through local PHAs that cover the difference between 30 percent of a household's adjusted gross income and a payment standard that reflects the cost of renting a unit that meets HUD's Housing Quality Standards (McClure, 2005).

Although voucher recipients are required by HUD program rules to spend no more than 40 percent of their income when entering the program or moving to a new unit, research finds that more than 16 percent of HCV participants experienced housing cost burdens in excess of 40 percent in 2002 (McClure, 2005). This article relies on cross-sectional and longitudinal data constructed from HUD administrative files to characterize the prevalence of housing cost burden over the 2003-to-2015 period, explore longitudinal trajectories of voucher recipients who initially leased a unit in 2003, and examine the marginal impact of various factors on the odds of a HCV household experiencing a housing cost burden in 2015. These analyses are designed to address different aspects of the following research question: how do HUD program rules influence HCV housing cost burdens? The findings suggest that certain provisions of the HCV program play an important role in shaping housing cost burdens, particularly local payment standards and the restriction on housing cost burden monitoring to those recently admitted or recently moved.

The article is organized as follows. The next section examines relevant literature addressing recent trends in housing cost burden for U.S. households and HCV renters. Following the literature review, we discuss the data and methods, present the research findings, and conclude with a summary of the most important findings and their policy implications.

Background

Rising rents and falling renter incomes have contributed to a rental housing crisis in American cities. Rental prices peaked in 2007, steadily declined through 2007 and 2010, and have risen since (JCHS, 2017). DiPasquale and Murray (2017) found that between 1970 and 2010, incomes fell for renters in all but the highest income quintile. Between 2000 and 2010, incomes for renters in the lowest income quintile fluctuated, falling by 12 percent between 2000 and 2005, rising by 7 percent between 2005 and 2008, and falling again by 6 percent between 2008 and 2010. During the housing recession, changes in income and household composition played particularly important roles in shaping renters' cost burden trajectories (Colburn and Allen, 2018).

We know little about how voucher-assisted renters fared during the recent housing market boom-bust cycle. The most recent detailed analysis of housing cost burden in the HCV program conducted prior to the housing market recession found that, although HCV-assisted households' cost burdens were on the decline, 38 percent of HCV program participants in 2002 spent more than 31 percent of their income on housing costs, and 17 percent spent more than 40 percent of their income on housing costs (McClure, 2005). Williamson (2011) examined data from a sample of about 38,000 households residing in Florida's Low-Income Housing Tax Credit (LIHTC) properties and found that about 35 percent of LIHTC residents receiving vouchers spent more than 30 percent of household income on rent. Leopold et al. (2015) conducted a more recent analysis of HUD administrative data (from 2013) and found that 42 percent of voucher recipients earning extremely low incomes spend more than 30 percent of income on rent.

Because the HCV program is designed to reduce housing cost burdens for qualifying low-income households, why do so many voucher recipients incur high housing cost burdens? Households may choose to spend a larger proportion of their income on rent to obtain housing that is higher quality, larger, or located in more desirable neighborhoods. If higher cost burdens are associated with improved neighborhood quality, then a voucher recipient's realization of these benefits may be a positive policy outcome. Even short-term gains in access to certain local public goods, such as high-quality schools, may yield long-term gains in a child's future economic opportunities and well-being. However, if these initially higher cost burdens persist or rise over time as rents rise relative to household incomes, households may be unable to remain in their chosen housing unit to take advantage of beneficial neighborhood amenities and services.

Certain types of households may be more likely to incur higher housing cost burdens than others. McClure (2005) found that among all voucher recipients, housing cost burden is particularly high for single-parent female-headed households, larger families with children (who need larger units), and those with extremely low incomes. It is possible that low-income families with children are more strongly "tied" to location, due to reliance on local social networks for social support and financial assistance (Dawkins, 2006). Likewise, non-White households may experience housing market discrimination, limiting their ability to move to adjust housing costs. This latter explanation is consistent with McClure's (2005) finding that households headed by African-Americans are more likely than other households to spend more than 40 percent of their income on rent.

Supply-side conditions may also influence households' ability to reduce housing cost burdens upon residential mobility. Pendall (2000) found that households receiving tenant-based rental assistance are more concentrated in distressed neighborhoods when those neighborhoods have a higher concentration of rental housing, despite such households' tendency to avoid neighborhoods with very low rents. Another factor is landlords' reluctance to participate in the HCV program. Unless states or localities have adopted legislation prohibiting the discrimination against those receiving tenant-based assistance, landlords' participation in the HCV program is purely voluntary, and many landlords choose not to participate due to perceived administrative barriers or other considerations (Freeman, 2011).

HUD program rules and administrative procedures may also play a role in shaping HCV housing cost burdens. Local PHAs may prioritize admissions to households that are more or less likely to incur higher housing cost burdens over time. The Quality Housing and Work Responsibility Act of 1998[1] (QHWRA) expanded the discretionary authority of local PHAs and set threshold requirements for the incomes of those newly admitted to HUD programs. Since 1998, PHAs have been required to ensure that 75 percent of new voucher holders have incomes no greater than 30 percent of the AMI and that all assisted households spend no more than 40 percent of income on housing costs at the time of lease up. Beyond these requirements, PHAs have substantial discretion to prioritize assistance to different types of households. Some PHAs place priority on housing those in greatest need, whereas others place emphasis on housing those most able to move to achieve greater self-sufficiency (Devine et al., 2000). Dawkins (2007) found that since the enactment of QHWRA, PHAs increasingly have been admitting smaller families headed by older adults and fewer extremely low-income female-headed households with children, thus signaling a trend away from the types of households identified by McClure (2005) who are most likely to incur high housing cost burdens.

For those households admitted to the HCV program, HUD policies determine the subsidy payment to renters and the range of housing units from which households may choose. Prior to selecting a unit, local PHAs determine the minimum tenant payment for an HCV household, or total tenant payment (TTP), which is equal to the greater of: (1) 30 percent of monthly adjusted income, (2) 10 percent of monthly gross income, (3) the welfare rent (in as-paid states only), or (4) a minimum rent payment as determined by the local PHA. Households may contribute more than 30 percent of their income toward rent but not more than 40 percent of monthly adjusted income upon entering the HCV program or signing a new lease (HUD, 2001). Thus, at the time of initial admission or lease up, HCV-assisted renters' cost burdens are effectively constrained to be between 30 and 40 percent of household income.

After a household's minimum and maximum contribution is determined, the household selects a unit, and the rent subsidy contributed by the local PHA hinges crucially on whether the rent for the selected unit is higher or lower than the payment standard established by the local PHA (generally equal to 90 to 110 percent of the metropolitan area Fair Market Rent [FMR]). If gross rent (contract rent plus any utility allowance) is equal to or lower than the payment standard, then housing cost burden is equal to (TTP/income). In this case, since TTP is usually equal to 30

[1] "Quality Housing and Work Responsibility Act of 1998; Initial Guidance," FR–4434–N–01. *Federal Register* 64 (32) February 18, 1999.

percent of a household's adjusted monthly income, the cost burden would always be 30 percent or lower, regardless of the level of the payment standard. However, if gross rent is higher than the payment standard, cost burden is equal to ([gross rent – payment standard + TTP] / income). If rent is initially above the payment standard and increases over time, housing cost burden will always increase unless the payment standard is adjusted or the PHA determines that rent increases are unreasonable, based on a rent-reasonableness evaluation.

Existing research points to two unresolved questions pertaining to the influence of these HUD program rules on HCV cost burdens. First, to what extent are households' higher housing cost burdens driven by the selection of housing units priced above the local payment standard? McClure (2005) found that a large percentage of HCV households incurring cost burdens are served by PHAs that establish local payment standards below 90 percent of FMR, but his analysis does not identify whether households served by these PHAs are actually more likely to choose housing units above the payment standard. Second, do households newly admitted to the HCV program and those moving to a new unit incur lower cost burdens than other HCV program participants? Per HUD program rules, households are not required to comply with the 40-percent cap on housing cost burdens after their initial lease period. Although PHAs monitor annual adjustments to income and rents after a household signs a new lease, PHAs have limited ability to influence the rent charged by local landlords beyond the "rent reasonableness" evaluation. In hot housing markets, high percentage increases in rent may be consistent with prevailing market rents. HUD does not specify the methodology that local PHAs must follow when conducting rent-reasonableness evaluations, and some local PHAs do not conduct rent reasonableness evaluations on a regular basis (Turnham and Khadduri, 2001; Varady, Wang, and Mittal, 2007). Furthermore, a local PHA's ability to increase rent subsidies is budget-constrained, and any increase in rent subsidies reduces the number of additional vouchers that can be awarded. Although HUD adjusts tenant payments in response to income changes upon annual reexaminations, these adjustments may not keep pace with changes in income if income streams vary from month to month.

In the analyses that follow, we address this gap in existing research by addressing the following research question: how do HUD program rules influence HCV housing cost burdens? We pay particular attention to the two features of HUD program rules discussed previously. First, we examine how renting units above the payment standard contributes to housing cost burden. Second, we examine whether those newly admitted to the HCV program or those recently moving to a new unit are less likely to incur cost burdens in excess of 40 percent of income.

Data and Methods

This research relies on administrative data from HUD's Public and Indian Housing Information Center system to examine trends in HCV housing cost burden between 2003 and 2015. The data are assembled from tenant-level databases collected from the HUD-50058 Family Report form completed by local PHAs.

We rely on two primary databases for the analyses. The first database is a set of cross-sectional household-level files for each year between 2003 and 2015. These files (one for each year) include the last household record available for each household in each year for all households that successfully leased up during or prior to the year in question. Households with zero income, those that receive project-based vouchers, and those that receive vouchers from Moving to Work (MTW) PHAs are excluded from the analyses. Using these databases, we examine trends in housing cost burden over time for all HCV-assisted households. For those participating in the HCV program in the most recent period (2015), we estimate logistic regression models to examine the marginal impact of various household, housing unit, and geographic characteristics on the odds of a HCV household experiencing a housing cost burden.

We also construct a longitudinal file of those who leased up in 2003. We follow these households over time, appending observations on rental spells for each year after initial lease up until either 2015 or the year in which the household exits from the HCV program. Using this database, we examine the duration of housing cost burden, emphasizing factors associated with different housing cost burden trajectories.

In all analyses, we define housing cost burden as the ratio of the family's total contribution to housing payments (gross rent minus the household's HAP) to the household's total annual adjusted gross income. Gross rent is equal to the contract rent plus a utility allowance. HAP is defined as the lower of gross rent or the payment standard minus the TTP. We use the terms *rent burden* and *housing cost burden* interchangeably throughout the article to reflect the percentage of income spent on housing costs. We categorize housing cost burdens into the following cost burden categories: no cost burden (spending 30 percent or less of income on housing costs), moderate cost burden (spending 31 to 40 percent of income on housing costs), high cost burden (spending 41 to 50 percent of income on housing costs), and severe cost burden (spending 51 percent of income or higher on housing costs). The so-called "30 percent rule" is a standard threshold level of housing cost burden that can be traced to the Brooke Amendment to the 1968 Housing and Community Development Act.[2] Because voucher recipients are required to spend no more than 40 percent of income on housing upon lease up, we use the 40-percent threshold to define the second housing cost burden threshold. The 50-percent threshold corresponds to HUD's definition of severe cost burden in its Worst Case Housing Needs reports.

Findings

The discussion of research findings is organized according to three different types of analyses. The first section below examines information from the cross-sectional household-level files for each year between 2003 and 2015. The second section examines information from the longitudinal database of those households that leased up in 2003 to examine housing cost burden trajectories. The third section relies on information from the cross-sectional file of households that leased up during or prior to 2015 to estimate logistic regression models that explain the marginal impact of various household, housing unit, and geographic characteristics on the odds of an HCV household experiencing a housing cost burden. Each of these analyses addresses different aspects of the following overarching research question: how do HUD program rules influence HCV housing cost burdens?

[2] Housing and Community Development Act of 1969, Section 213(a). Pub. L. 91–152. December 24, 1969.

Prevalence of HCV Housing Cost Burden Over Time

Exhibit 1 displays, for each year, the total number of HCV households spending 30 percent or less of their income on rent, 31 percent or more of income on rent, between 31 and 40 percent of income on rent, between 41 and 50 percent of income on rent, 51 percent or more of income on rent, and the total number of households. Exhibit 2 displays the percentage of households falling into each of these housing cost burden categories by year (excluding the "any cost burden" category). The total sample sizes (after excluding those with project-based vouchers, those with zero income, and those served by MTW PHAs) range between 1.6 and 1.7 million households, depending on the year.

Exhibit 1

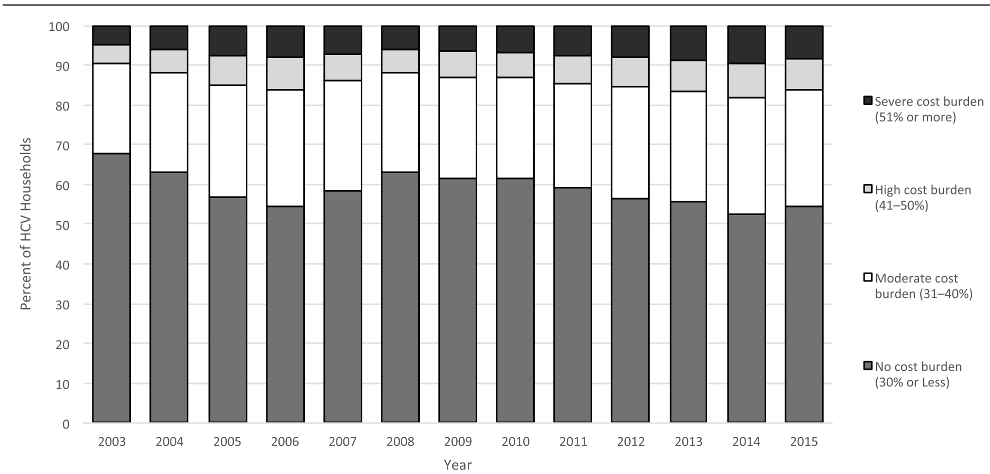
HCV Households by Extent of Housing Cost Burden, 2003–2015

	No Cost Burden (30% or Less)	Any Cost Burden (31% or More)	Moderate Cost Burden (31–40%)	High Cost Burden (41–50%)	Severe Cost Burden (51% or More)	Total
2003	1,095,683	517,665	360,794	78,500	78,371	1,613,348
2004	1,011,929	590,988	400,695	95,364	94,929	1,602,917
2005	904,844	684,472	447,381	117,583	119,508	1,589,316
2006	909,791	765,417	496,044	134,108	135,265	1,675,208
2007	999,470	710,429	473,754	116,054	120,621	1,709,899
2008	1,095,772	644,484	435,053	101,988	107,443	1,740,256
2009	1,066,702	666,378	440,855	110,858	114,665	1,733,080
2010	1,070,330	671,092	444,345	109,283	117,464	1,741,422
2011	1,033,761	716,661	460,935	123,229	132,497	1,750,422
2012	986,171	760,437	490,866	130,585	138,986	1,746,608
2013	952,359	755,471	472,499	136,247	146,725	1,707,830
2014	893,875	811,315	499,697	149,189	162,429	1,705,190
2015	941,798	786,958	505,710	136,846	144,402	1,728,756

HCV = Housing Choice Voucher.

Exhibit 2

Proportion of HCV Households With Specified Housing Cost Burden, 2003–2015



HCV = Housing Choice Voucher.

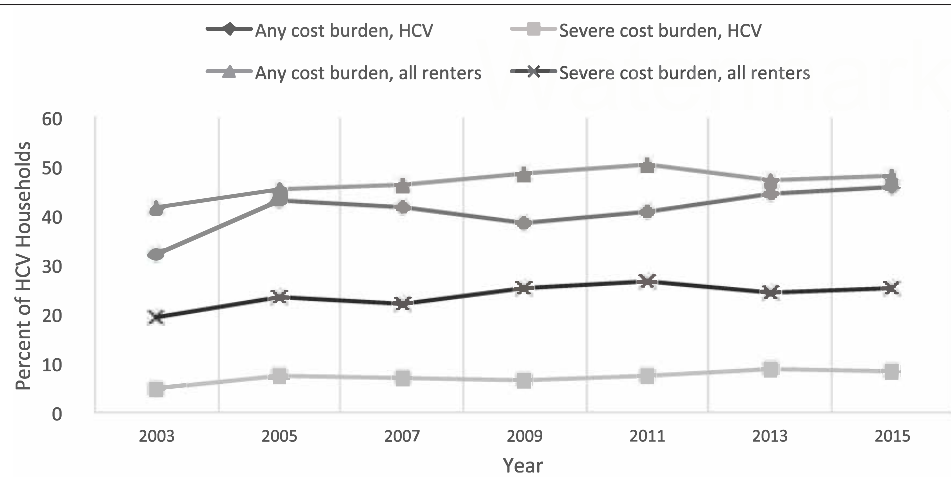
Although the total number of HCV-assisted households has remained essentially flat over the 2003-to-2015 period, the total number of cost-burdened HCV households has increased by 52 percent from 517,665 in 2003 to 786,958 in 2015 (the number of cost-burdened households reached a high of 811,315 in 2014 but fell slightly in 2015). As a share of total HCV households in each year, those experiencing any level of cost burden increased by 13 percentage points, those experiencing moderate cost burdens increased by 7 percentage points, those experiencing high cost burdens increased by 3 percentage points, and those experiencing severe cost burdens increased by 4 percentage points.

The year-to-year change in housing cost burden roughly corresponds to the recent housing market boom-bust cycle. The share of HCV households experiencing housing cost burdens rose to a peak of 46 percent of households in 2006, followed by a steady decline during the housing bust. As the housing market began to recover, the share of cost-burdened HCV households rose again to a higher peak of 48 percent in 2014. These trends suggest that the increase in rental affordability during the initial years of the housing recession temporarily reduced housing cost burdens, but by 2015, housing cost burdens had risen to prerecession levels.

To provide additional context for the drop in housing cost burden during the housing bust, exhibit 3 compares the percentage of HCV renters that experienced a cost burden or a severe cost burden with the percentage of all U.S. renters experiencing the same levels of cost burden over the 2003-to-2015 period as reported in the *2017 Worst Case Housing Needs* Report. As this figure illustrates, the gap in housing cost burden between HCV renters and all U.S. renters widened between 2005 and 2013. One possible explanation for the cost burden gap between HCV households and all U.S. renters is that the trends in exhibits 2 and 3 were driven by newly admitted HCV households that were more likely to incur lower cost burdens. Although there was an influx of newly admitted voucher recipients during the housing bust, new admissions never comprised more than about 10 percent of all HCV program participants in any given year.

Exhibit 3

Housing Cost Burdens for HCV Households and U.S. Renters, 2003–2015



HCV = Housing Choice Voucher.

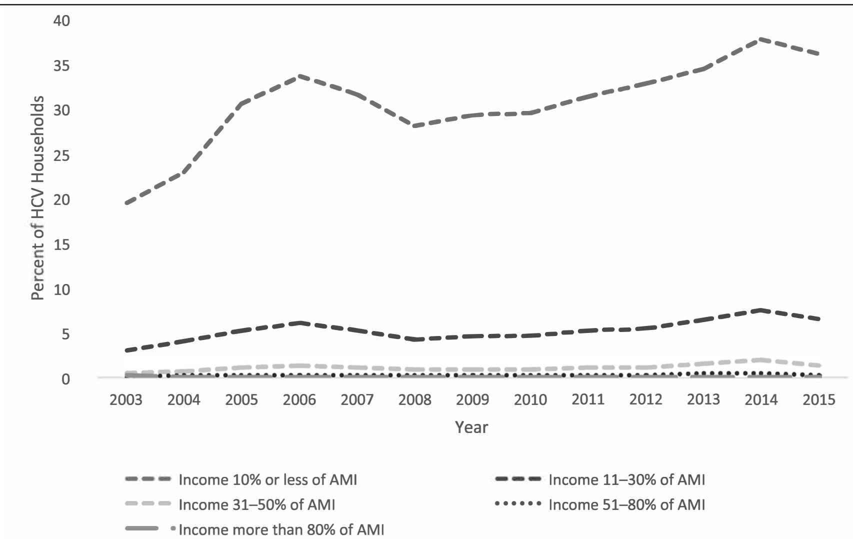
Another possible explanation for the trends in exhibits 2 and 3 is that vouchers provided a stable source of rent payment for voucher recipients that insulated these households from job loss or income shocks. This explains why housing cost burdens did not rise during the housing bust, but it does not fully explain why HCV cost burdens declined. For housing cost burdens to fall for HCV renters, rents must also have declined. In response to job losses and rising unemployment rates especially among young workers, vacancy rates rose, and real rents fell in most housing markets during the housing bust (DiPasquale, 2011). Since moving is generally less costly for renters than for owners, renters could more easily respond to changes in employment and housing market conditions, leading to downward pressure on rents in areas hit hardest by the housing bust. Collinson (2011) found that between 2007 and 2010, rents fell by 6 to 8 percentage points in the housing markets that were hit hardest by foreclosures.

How does housing cost burden vary with income? HUD annually establishes income limits by family size for its assisted housing programs that are based on AMI of the surrounding FMR area, which is typically coincident with the U.S. Census Bureau-defined metropolitan area for that year. As of 2015, the majority of HCV households in the sample (61 percent) had incomes between 11 and 30 percent of AMI, 11 percent had incomes less than 10 percent of AMI, and the remainder had incomes more than 30 percent of AMI. Among those with incomes less than 10 percent of AMI, 61 percent experienced a housing cost burden and 36 percent experienced a severe housing cost burden in 2015. Also, among those earning $5,000 or less, 65 percent experienced a housing cost burden, and 40 percent experienced a severe housing cost burden.

Exhibit 4 displays the percentage of households within different income ranges that experienced severe housing cost burdens (51 percent or more) in each year. The gap in severe housing cost burdens between those with incomes of 10 percent or less of AMI and those with incomes of more

Exhibit 4

Prevalence of Severe Housing Cost Burden by Income as a Percent of AMI, 2003–2015



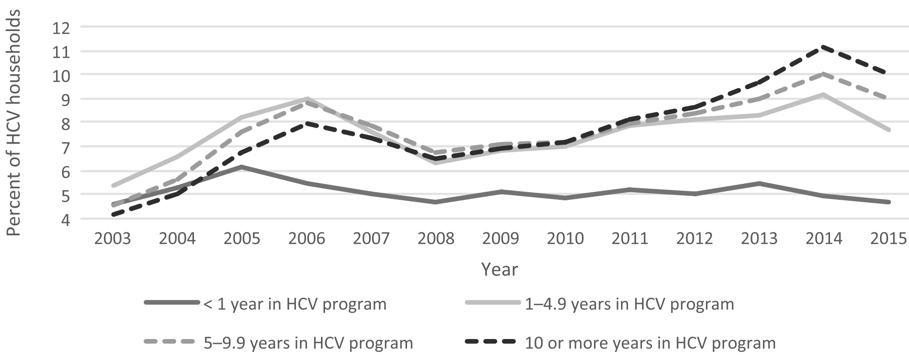
AMI = Area Median Income. HCV = Housing Choice Voucher.

than 80 percent of AMI has grown over time from 35 percentage points in 2003 to 47 percentage points in 2015. It is notable that in all years but 2003, more than 20 percent of those with incomes of 10 percent or less of AMI experienced cost burdens of 51 percent or higher, a level of cost burden that is inconsistent with HCV program goals.

The discussion in the previous section suggests that those newly admitted to the HCV program may incur lower housing cost burdens, due to HUD's 40-percent cap on housing cost burdens. Exhibit 5 displays the percentage of households that incur severe housing cost burdens by the number of years of program participation. After 2005, those newly admitted to the HCV program experienced consistently lower housing cost burdens than those who had been in the program for a longer period of time, and the gap between those newly admitted and those with longer HCV program durations generally grew over time.

Exhibit 5

Prevalence of Severe Housing Cost Burden by Length of Program Participation, 2003–2015



HCV = Housing Choice Voucher.

HCV Housing Cost Burden Trajectories

For how long do voucher recipients remain in a cost-burdened state, and how does residential mobility and the selection of a unit above the payment standard contribute to the duration of cost burden? To address this question, we rely on information from a longitudinal file of those who leased up in 2003. We follow these households over time, appending observations on rental spells for each year after initial lease up until either 2015 or the year in which the household exits from the HCV program. Using this database, we examine several descriptive statistics related to housing cost burden trajectories, including—

- Average total duration in the HCV program (years).
- Average duration in cost burden (years), separately by level of cost burden experienced.
- Percentage of households cost burdened at the beginning of the voucher contract by severity of cost burden.
- Percentage of households cost burdened at least 1 year by severity of cost burden.

- Percentage of households cost burdened consecutively throughout the voucher contract, by severity of cost burden, separately for those who never moved and those who moved at least once since initial lease up.
- For those who moved at least once, the average number of moves and percentage of households that increased (decreased) cost burden upon mobility.

Exhibit 6 reports each of these longitudinal statistics for those that initially leased a unit in 2003. The statistics are further disaggregated by the household's initial rent payment vis-à-vis the payment standard. On average, households that initially leased a unit in 2003 participated in the HCV program for about 6 years. Approximately 2 of those years were spent in a cost-burdened state, but for those renting a unit priced above the payment standard (73,045 or about 36 percent of all households), nearly 4 years are spent in a cost-burdened state.

Exhibit 6

Longitudinal Statistics for HCV Households That Leased a Unit in 2003

	All HCV Households	Rent ≤ Payment Standard	Rent > Payment Standard
All HCV households	204,213	131,168	73,045
Average total duration (years)	6.3	6.4	6.1
Average duration in cost burden (years)	2.4	1.7	3.8
Average duration in high cost burden (years)	0.8	0.6	1.1
Average duration in severe cost burden (years)	0.4	0.4	0.5
Cost burdened at beginning of the voucher contract (%)	37.3	5.3	94.7
High cost burdened at beginning of the voucher contract (%)	5.7	3.5	9.6
Severely cost burdened at beginning of the voucher contract (%)	3.1	2.6	4.1
Cost burdened at least 1 year (%)	64.3	46.1	97.0
High cost burdened at least 1 year (%)	30.3	24.0	41.7
Severely cost burdened at least 1 year (%)	18.0	15.4	22.6
Cost burdened throughout the voucher contract (%)	16.4	1.7	42.7
High cost burdened throughout the voucher contract (%)	1.8	0.9	3.5
Severely cost burdened throughout the voucher contract (%)	0.9	0.6	1.4
HCV households that never moved	165,121	105,315	59,806
Cost burdened throughout the voucher contract (%)	19.1	2.0	49.1
High cost burdened throughout the voucher contract (%)	2.2	1.1	4.2
Severely cost burdened throughout the voucher contract (%)	1.1	0.7	1.7
All HCV households that moved since initial lease up	39,092	25,853	13,239
Average number of moves	1.4	1.4	1.4
Reduced cost burden upon mobility (%)	42.5	37.7	51.8
Increased cost burden upon mobility (%)	45.5	47.5	41.5
Cost burdened throughout the voucher contract (%)	4.9	0.6	13.5
High cost burdened throughout the voucher contract (%)	0.3	0.2	0.4
Severely cost burdened throughout the voucher contract (%)	0.1	0.1	0.1

HCV = Housing Choice Voucher.

A substantial share (37 percent) of HCV households experienced some level of cost burden, and about 3 percent experienced severe cost burdens. Since program rules preclude households from spending more than 40 percent of their income on rent at the time of lease up, this latter percentage suggests that some PHAs are not adequately monitoring and enforcing compliance with the HUD program rules. Among those renting a unit above the payment standard, nearly all (95 percent) are cost burdened upon initial lease up.

For all HCV households, 64 percent experienced a cost burden of at least 1 year or longer, and this percentage is particularly high among those initially renting a unit priced above the payment standard. Of households, 18 percent experienced a severe housing cost burden for at least 1 year. Because even a single year of high housing cost burden may spur housing instability, due to the financial pressures of moving and finding a lower cost unit, this high level of exposure to temporary cost burdens is particularly troublesome.

Our primary metric of the impact of mobility on cost-burden trajectories is the percentage of households that are cost burdened consecutively throughout their participation in the HCV program. For all households, approximately 16 percent of households fell into this category, but among those renting a unit priced above the payment standard, 43 percent were consecutively cost burdened. Mobility plays an important role in reducing exposure to consecutive cost burdens, as revealed by the statistics shown in the bottom of exhibit 6. Whereas 19 percent of households that never moved were consecutively cost burdened, less than 5 percent of those who moved since lease up were consecutively cost burdened. Among those living in a unit priced above the payment standard, the difference between movers and stayers is even larger (14 versus 49 percent). Given that only about 20 percent of households entering the program in 2003 subsequently moved to another unit, the long duration of cost burden among stayers is particularly troublesome. Although a slightly higher percentage of those who moved increased rather than reduced housing cost burdens upon mobility (46 versus 43 percent), those initially leasing a unit above the payment standard were more likely to reduce their cost burden upon mobility, whereas those initially leasing a unit below the payment standard were more likely to increase their cost burden upon mobility.

Determinants of HCV Housing Cost Burdens

In this section, we examine the marginal contribution of various household, housing unit, and geographic factors on the odds of having any cost burden, a high cost burden, or a severe cost burden in 2015 using logistic regression models. In contrast to the longitudinal analysis described in the previous section which described longitudinal trends for those who entered the HCV program and leased a unit in 2003, the analysis described here reveals the determinants of housing cost burdens for those participating in the HCV program in the most recent period for which data are available (2015).

In the logistic regression models, the dependent variable is equal to 1 if a household has a cost burden of a given level or higher and 0 otherwise. Independent variables include various factors shown in the literature to be correlated with high housing costs, including family composition, disability, age of household head, race and ethnicity of household head, income (as a percentage of AMI), and source of income. We also control for various characteristics of the housing unit selected by the voucher recipient, including number of bedrooms, housing type, and housing age. Finally, we include various controls to capture geographic variation in regional and neighborhood (census tract) housing market conditions. The estimated regression models can be roughly interpreted as Engel curves, named for the statistician Ernst Engel, who relied on Belgian survey data to demonstrate how household food expenditure data varied with income. Regression models based on this approach typically explain expenditure shares on a given commodity as a function of income and other demographic determinants of demand (Leser, 1963; Working, 1943).

The key policy variables are an indicator of whether the household has selected a unit with a rent above the payment standard and an indicator of whether the household falls into the category of those who are monitored by HUD for compliance with the 40-percent-of-income cap. Those falling into the 40-percent cap compliance category include all recently admitted to the HCV program and all recent movers. We should note that recent mobility may influence cost burden for reasons independently of program compliance requirements. Due to the presence of mobility costs, recent movers are more likely to be in equilibrium with respect to their most preferred housing bundle compared to nonmovers (Weinberg, Friedman, and Mayo, 1981). This implies that the estimates for the HUD program compliance indicator will reflect both a pure programmatic impact and any associated impacts due to recent mobility. Although our estimates should be interpreted with this qualification in mind, no reason exists to expect that the impacts of recent mobility should exhibit a threshold at the level of 40 percent of income. For this reason, we place emphasis on differences in the impact of recent mobility and recent program admission at the 40-percent cost-burden level relative to other thresholds.

We also control separately for length of HCV program participation, because program participation duration may reflect other unobserved household-level determinants of housing cost burden. For example, we might expect those with shorter HCV program durations to be more likely to rely on HCV assistance to address temporary conditions of housing instability, perhaps induced by short-term job loss or changes in family status, compared to long-term program participants who may be more heavily reliant on housing and other forms of governmental assistance. The models are estimated for the most recent period for which data are available (2015). Exhibit 7 provides a detailed description of the variable definitions and descriptive statistics for all variables used in the model, and exhibit 8 provides estimates of the logistic regression coefficients for the base models for the three different cost-burden thresholds.

The results displayed in exhibit 8 suggest that the determinants of housing cost burden differ by level of cost burden. This difference is likely due to the impact of differential programmatic requirements at different cost-burden thresholds. Since most HCV households are required to spend at least 30 percent of adjusted monthly income on rent, few will fall below this threshold, and those that do are likely to exhibit unique characteristics that exempt these households from HUD's minimum tenant payment requirements. For example, households with zero household income often receive special considerations in the calculation of cost burden, and HUD grants exceptions to minimum contribution requirements in cases of special hardship (HUD, 2001). Likewise, HUD's 40-percent-of-income cap places an upper limit on housing cost burdens for most households. The only possible explanations for incurring cost burdens above this threshold are: (1) not having recently moved or recently entered the program, (2) exceptions to the 40-percent-of-income cap granted by local PHAs, or (3) inadequate program monitoring on the part of local PHAs.

Exhibit 7

Descriptive Statistics and Variable Definitions for Logistic Regression Models

Variable	Definition	Mean	Std Dev
Dependent variable			
Any cost burden	1 = A household experiences any cost burden (31% or more)	0.46	0.50
High cost burden	1 = A household experiences a high cost burden (41% or more)	0.16	0.37
Severe cost burden	1 = A household experiences a severe cost burden (51% or more)	0.08	0.28
Independent variables			
Rent and income			
Rent above the payment standard	1 = Gross rent above the payment standard	0.44	0.50
Income as % of AMI	1 = Total annual income 10% of less than AMI 2 = Total annual income 11–30% of AMI 3 = Total annual income 31–50% of AMI 4 = Total annual income 51–80% of AMI 5 = Total annual income more than 80% of AMI	2.19	0.78
Household characteristics			
Newly admitted or moved to a new unit	1 = New to the program or moved into a new unit	0.10	0.30
Length of participation	Length of participation (years)	7.94	6.68
Household size	Number of household members	2.39	1.58
Children	1 = A household has at least one child	0.47	0.50
Female	1 = A household head is female	0.81	0.39
Elderly	1 = A household head is elderly	0.22	0.41
Disabled	1 = A household head is disabled	0.27	0.44
Primarily wage	1 = Primary source of income is wage	0.31	0.46
Non-White	1 = A household head is non-White	0.51	0.50
Hispanic	1 = A household head is Hispanic	0.17	0.37
Housing unit type			
Bedroom	Number of bedrooms	2.14	0.96
Single-family	1 = Single-family (detached/attached) home	0.59	0.49
Building age	Age of housing unit (years)	46.75	33.34
Geography			
Midwest	1 = Midwest (Census region)	0.20	0.40
South	1 = South (Census region)	0.35	0.48
West	1 = West (Census region)	0.21	0.41
Metropolitan—central city	1 = Central city, metropolitan area	0.48	0.50
Metropolitan—suburb	1 = Suburb, metropolitan area	0.39	0.49
Micropolitan	1 = Micropolitan area	0.08	0.27
Neighborhood characteristics			
Median rent	Census-tract level median gross rent	896.79	295.55
Median rent above the FMR	1 = A census tract's median gross rent is above the FMR	0.30	0.46
Vacancy rate	Census-tract level vacancy rate	11.88	8.08
Poverty rate	Census-tract level poverty rate	21.77	13.09
% Minority population	Census-tract level percentage of minority population	53.24	32.34
% Housing voucher recipients	Census-tract level percentage of housing voucher recipients out of all renters	12.71	10.30

AMI = Area Median Income. FMR = Fair Market Rent. Std Dev = standard deviation.

Exhibit 8

Factors Associated With the Odds of a Housing Cost Burden, 2015 (Base Model)

Category	Explanatory Variable	Any Cost Burden	High Cost Burden	Severe Cost Burden
Rent and income				
	Rent above the payment standard	7.685***	2.925***	2.328***
	Income as % of AMI	– 1.538***	– 1.573***	– 2.278***
Household characteristics				
	Newly admitted or moved to a new unit	0.119***	– 1.547***	– 1.140***
	Length of participation	– 0.012***	0.018***	0.020***
	Household size	– 0.129***	– 0.301***	– 0.347***
	Children	– 0.129***	– 0.159***	– 0.150***
	Female	– 0.037***	0.078***	0.078***
	Elderly	– 1.267***	– 0.699***	– 0.699***
	Disabled	– 1.420***	– 0.730***	– 0.662***
	Primarily wage	– 0.876***	– 0.446***	– 0.457***
	Non-White	0.093***	0.030***	0.052***
	Hispanic	– 0.056***	0.075***	0.101***
Housing unit type				
	Bedroom	0.184***	0.548***	0.678***
	Single-family	– 0.039***	0.102***	0.109***
	Building age	– 0.000***	– 0.000***	0.000
Geography				
	Midwest	– 0.268***	0.004	– 0.022*
	South	– 0.130***	0.171***	0.177***
	West	– 0.364***	0.051***	0.084***
	Metropolitan—central city	0.210***	0.028*	0.083***
	Metropolitan—suburb	0.004	– 0.136***	– 0.119***
	Micropolitan	0.126***	– 0.060***	– 0.035
Neighborhood characteristics				
	Median rent	0.000	0.000***	0.001***
	Median rent above the FMR	0.179***	0.099***	0.100***
	Vacancy rate	0.006***	– 0.002***	– 0.002***
	Poverty rate	0.001***	– 0.000	– 0.000
	% Minority population	0.001***	0.002***	0.003***
	% Housing voucher recipients	0.008***	– 0.001***	– 0.001**
Constant		0.472***	– 1.002***	– 0.813***
Number of observations		1,696,116	1,696,116	1,696,116
Wald chi-square		407,228.33***	316,297.75***	194,781.55***
Pseudo R^2		0.775	0.336	0.346

*** $p < 0.01$. ** $p < 0.05$. * $p < 0.1$.
AMI = Area Median Income. FMR = Fair Market Rent.
Note: Northeast and Rural are omitted.

In the models explaining the probability of a high or severe cost burden, the households most likely to suffer housing cost burdens include those without children, those headed by females, those with nonelderly household heads, those without disabled household heads, those headed by non-White household heads, those headed by Hispanic household heads, those reliant on government sources of income, and those earning lower incomes. The lower incidence of housing cost burden among households headed by a person with a disability is somewhat surprising, given evidence that such households are more likely to incur high housing cost burdens (Souza et al., 2011). One possible explanation is that rents are more stable in housing units specifically targeted to persons with a disability, particularly if other HUD place-based programs subsidize rents. This finding deserves further exploration.

The higher incidence of housing cost burden among female-headed and non-White households is consistent with McClure (2005), but in contrast with McClure we find that households without children are more likely to exhibit housing cost burdens than households with children. In a separate longitudinal analysis not reported here, we found that the prevalence of severe housing cost burden by household size has varied over time. In 2006, at the height of the housing boom, 8.4 percent of large households (five or more persons) experienced severe housing cost burdens, and 5.0 percent of single-person households experienced severe housing cost burdens. This gap declined over time, and in 2015, the year under consideration in the logistic regression analysis, single-person households were slightly more likely than large households to incur severe housing cost burdens. This finding deserves additional exploration to determine the influence of changing household size and composition on housing cost burdens. It is possible that household size is not a determinant of but a response to high housing cost burden, as couples forgo the decision to have children if doing so is likely to impose a financial burden (Colburn and Allen, 2018).

Those living in larger single-family units are more likely to experience a high or severe housing cost burden. The effect of the number of bedrooms on the odds of a severe housing cost burden is more than three times larger than the effect of number of bedrooms on the odds of any housing cost burden. The influence of housing unit age varies by severity of cost burden.

Exhibit 8 also provides evidence of significant geographic variation in the determinants of housing cost burdens. Those living in the South are more likely to experience a housing cost burden than those living in other census regions. Regarding the intra-metropolitan location of households, those living in central cities experience the highest cost burdens, and those living in suburban areas experience the lowest cost burdens.

Various census tract-level characteristics shape housing cost burdens. Those living in census tracts with higher median rents, median rents above the FMR, and a higher percentage of minority residents exhibit higher housing cost burdens. After controlling for other census tract-level variables, census tract poverty rates do not influence high or severe cost burdens at statistically significant levels, although high poverty rates are associated with a lower probability of having any cost burden. The finding that the probability of high and severe cost burdens is negatively associated with vacancy rates, and the percentage of census renters receiving vouchers is consistent with the prevailing wisdom among housing policy practitioners that the HCV program is most effective in loose housing markets with high vacancy rates and a healthy supply of properties managed by landlords that accept vouchers.

The key policy variables of interest—rent above the payment standard and newly admitted or moved to a new unit—are both consistent with expectations. Those households initially paying a rent above the payment standard are much more likely to exhibit housing cost burdens at any level. Furthermore, those recently admitted to the HCV program or that have recently moved to a new unit are less likely to exhibit high and severe housing cost burdens. The differences in the sign of the new admission-recent mover coefficient between any cost burden and high or severe cost burdens suggest that HUD income caps effectively constrain households to spend within 30 and 40 percent of their income on housing when signing a new lease or entering the program. If compliance with this provision is taken as a metric of success, then the HCV program appears to be operating as expected. It is also interesting to note that after controlling for the categorical distinction between recent movers or recent admissions and other households, length of program participation is positively associated with high and severe housing cost burdens. This finding combined with the large reduction in housing cost burden associated with the receipt of income from wages suggests that households not able to work and confined to fixed incomes from different sources of government assistance are more likely to be cost burdened.

In addition to its direct impact on the probability of a housing cost burden, the categorical programmatic distinction between new movers or new admissions and other voucher recipients may also interact with other household, housing unit, and geographic variables to influence housing cost burden. To test this conjecture, exhibit 9 displays estimates from models stratified into new movers or new admissions versus all others. A key finding from this table is that renting above the payment standard has a different impact for new admissions or new movers versus others. In the model explaining the probability of a high housing cost burden (41 percent or higher), renting above the payment standard has little impact on new admissions or new movers, because these households are not allowed to take on this level of housing cost burden. Likewise, renting a unit above the payment standard actually reduces the probability of these households incurring a severe housing cost burden. For households not constrained by the HUD 40-percent-of-income requirement, the impact of renting a unit above the payment standard is positive and much larger in magnitude.

Exhibit 9 also suggests that the impact of household income is much smaller for those in the "other" category, particularly for cost burdens above the 40-percent threshold, because income changes for these households may be insufficient to offset the impact of rising rents in housing units already chosen. Several household and housing unit variables also have impacts that differ between the two samples. The magnitude of the impact of number of bedrooms on housing cost burden is much higher for those not recently admitted or recently moved, suggesting either that local PHAs are unsuccessful in adjusting rental subsidies to compensate for rising housing costs in larger units, or that mobility costs limit households' ability to adjust housing costs according to changing housing needs. The relatively higher incidence of high and severe cost burdens for non-White and Hispanic households in previous models is not statistically significant in the subsample of new admissions or new movers.

The influence of regional and census tract-level housing market characteristics also differs significantly between new admissions or new movers versus others. Although renting a unit above the FMR has a positive impact on housing cost burden across both samples, census tract median rents

Exhibit 9

Factors Associated With the Odds of a Housing Cost Burden, 2015 (Stratified Models) (1 of 2)

Category	Explanatory Variable	Newly Admitted or Moved to a New Unit			Others		
		Any Cost Burden	High Cost Burden	Severe Cost Burden	Any Cost Burden	High Cost Burden	Severe Cost Burden
Rent and income							
	Rent above the payment standard	7.627 ***	0.242 ***	– 0.304 ***	7.697***	3.127***	2.528***
	Income as % of AMI	– 1.676 ***	– 2.014 ***	– 2.734 ***	– 1.526***	– 1.566***	– 2.283***
Household characteristics							
	Length of participation	– 0.006 **	0.004	– 0.004	– 0.013***	0.018***	0.020***
	Household size	– 0.077 ***	– 0.032 **	0.021	– 0.134***	– 0.313***	– 0.361***
	Children	– 0.181 ***	– 0.280 ***	– 0.314 ***	– 0.120***	– 0.148***	– 0.132***
	Female	– 0.065 **	– 0.012	0.074 *	– 0.033***	0.086***	0.084***
	Elderly	– 1.261 ***	– 0.591 ***	– 0.558 ***	– 1.260***	– 0.698***	– 0.700***
	Disabled	– 1.377 ***	– 0.742 ***	– 0.696 ***	– 1.418***	– 0.725***	– 0.659***
	Primarily wage	– 0.866 ***	– 0.611 ***	– 0.729 ***	– 0.874***	– 0.439***	– 0.446***
	Non-White	0.064 **	0.012	0.025	0.098***	0.035***	0.057***
	Hispanic	– 0.138 ***	0.038	0.043	– 0.045***	0.081***	0.109***
Housing unit type							
	Bedroom	0.134 ***	0.122 ***	0.059 **	0.189***	0.570***	0.703***
	Single-family	0.074 ***	0.094 ***	0.048	– 0.058***	0.106***	0.115***
	Building age	0.001 **	0.001	0.001	– 0.001***	– 0.000***	0.000
Geography							
	Midwest	– 0.415 ***	– 0.323 ***	– 0.396 ***	– 0.251***	0.006	– 0.021*
	South	– 0.265 ***	– 0.193 ***	– 0.401 ***	– 0.114***	0.180***	0.193***
	West	– 0.559 ***	– 0.937 ***	– 1.084 ***	– 0.344***	0.081***	0.119***
	Metropolitan—central city	0.253 ***	– 0.249 ***	– 0.177 **	0.203***	0.061***	0.115***
	Metropolitan—suburb	0.011	– 0.482 ***	– 0.402 ***	0.001	– 0.106***	– 0.090***
	Micropolitan	0.190 ***	– 0.162 ***	– 0.068	0.111***	– 0.046**	– 0.029

Exhibit 9

Factors Associated with the Odds of a Housing Cost Burden, 2015 (Stratified Models) (2 of 2)

Category	Explanatory Variable	Newly Admitted or Moved to a New Unit			Others		
		Any Cost Burden	High Cost Burden	Severe Cost Burden	Any Cost Burden	High Cost Burden	Severe Cost Burden
Neighborhood characteristics							
	Median rent	– 0.000	– 0.000 ***	– 0.000 ***	0.000	0.000***	0.001***
	Median rent above the FMR	0.201 ***	0.155 ***	0.176 ***	0.176***	0.099***	0.099***
	Vacancy rate	0.004 ***	0.007 ***	0.009 ***	0.006***	– 0.003***	– 0.003***
	Poverty rate	0.005 ***	0.002 *	0.002	0.001*	– 0.001*	– 0.000
	% Minority population	– 0.001	0.001 ***	0.002 ***	0.001***	0.002***	0.003***
	% Housing voucher recipients	0.004 ***	0.000	0.001	0.009***	– 0.001***	– .001**
Constant		1.029 ***	1.458 ***	2.021 ***	0.427***	– 1.276***	– 1.067***
Number of observations		186,057	186,057	186,057	1,510,059	1,510,059	1,510,059
Wald Chi-Square		42,594.33 ***	13,472.68 ***	11,004.85 ***	365,554.96***	306,387.17***	179,201.01***
Pseudo R2		0.748	0.221	0.310	0.778	0.345	0.354

*** $p < 0.01$. ** $p < 0.05$. * $p < 0.1$.

AMI = Area Median Income. FMR = Fair Market Rent.

Note: Northeast and Rural are omitted.

negatively influence housing cost burden for new admissions or new movers. Similarly, cost burdens for others are more sensitive to local vacancy rates and the presence of other HCV households.

To get a better sense of the magnitude of the impacts displayed exhibits 8 and 9, exhibit 10 displays the predicted probability of a housing cost burden at different cost burden levels, allowing the household income, rent payment vis-à-vis the payment standard, and sample to vary, while holding other independent variables at their respective means. Exhibit 10 suggests that the probability of a housing cost burden at any level is highest for those with the lowest incomes. For those earning less than 10 percent of AMI, the probability of any cost burden is nearly 100 percent. For all income levels, the probability of a housing cost burden is higher for those renting a unit above the payment standard, but new admissions or new movers are substantially less likely to exhibit cost

Exhibit 10

Predicted Probabilities of Housing Cost Burden by Income and Rent Payment

Income	Full Sample		Newly Admitted or Moved to a New Unit	
	Rent ≤ Payment Standard	Rent > Payment Standard	Rent ≤ Payment Standard	Rent > Payment Standard
Predicted probabilities of any cost burden (%)				
Total annual income 10% or less than AMI	13.53	99.71	18.30	99.78
Total annual income 11–30% of AMI	3.25	98.65	4.02	98.85
Total annual income 31–50% of AMI	0.72	94.02	0.78	94.15
Total annual income 51–80% of AMI	0.15	77.15	0.15	75.07
Total annual income more than 80% of AMI	0.03	42.05	0.03	36.03
Predicted probabilities of high cost burden (%)				
Total annual income 10% or less than AMI	11.05	69.84	17.16	20.88
Total annual income 11–30% of AMI	2.51	32.44	2.69	3.40
Total annual income 31–50% of AMI	0.53	9.06	0.37	0.47
Total annual income 51–80% of AMI	0.11	2.02	0.05	0.06
Total annual income more than 80% of AMI	0.02	0.43	0.01	0.01
Predicted probabilities of severe cost burden (%)				
Total annual income 10% or less than AMI	10.58	54.84	14.01	10.72
Total annual income 11–30% of AMI	1.20	11.07	1.05	0.77
Total annual income 31–50% of AMI	0.12	1.26	0.07	0.05
Total annual income 51–80% of AMI	0.01	0.13	0.00	0.00
Total annual income more than 80% of AMI	0.00	0.01	0.00	0.00

AMI = Area Median Income.

burdens when renting above the payment standard than are others. For example, the probability of a severe housing cost burden for a recent mover or new admission who earns 10 percent or less of AMI and rents a unit above the payment standard is only 11 percent, and this probability is lower than those in the same group who rent a unit below the payment standard. By comparison, in the full sample, the probability of a severe housing cost burden for a household earning 10 percent or less of AMI and renting a unit above the payment standard is 55 percent.

Conclusion and Policy Implications

This study examined trends in housing cost burden for households participating in the HCV program during the 2003-to-2015 period. We found that the number and share of HCV households experiencing a housing cost burden has increased since 2003, and the year-to-year trend in HCV cost burden roughly corresponded to the recent housing market boom-bust cycle. We observed a dip in housing cost burden during the initial years of the housing market recession, which was likely induced by increased rental market affordability during this period. By 2015, 46 percent of HCV households experienced a cost burden of 31 percent or more, 16 percent experienced a cost burden of 41 percent or more, and 8 percent experienced a cost burden of 51 percent or more. Compared to McClure (2005), who examined cost burdens in 2002 just prior to our study period, the prevalence of housing cost burdens of 31 percent or more has increased from 38 percent in 2002 to 46 percent in 2015, whereas the percentage of those spending more than 40 percent of income on housing costs has remained approximately the same.

Cross-sectional and longitudinal analyses reveal that HUD program rules play an important role in shaping housing cost burdens, particularly HUD rules governing local payment standards and the restriction on the 40 percent-of-income cost burden cap to new admissions and recent movers. For all years since 2005, those households newly admitted to the HCV program were consistently less likely to exhibit severe housing cost burdens. Those renting a unit above the payment standard in 2003 were more likely to experience a cost burden at the beginning of the voucher contract and exhibit longer housing cost burden trajectories while participating in the HCV program. Residential mobility plays an important role in reducing the incidence of housing cost burdens throughout the HCV contract, despite households initially taking on higher housing cost burdens upon mobility.

These findings hold in logistic regression models explaining the determinants of housing cost burdens at different levels. Recent admissions and new movers are less likely to exhibit high or severe housing cost burdens and are less likely to incur a high or severe housing cost burden when renting above the payment standard. Recent admissions and new movers also respond differently than others to local housing market conditions. Simulations from the regression models suggests that among those earning the lowest incomes (10 percent of AMI), new movers and recent admissions are about 44 percent less likely to incur a severe housing cost burden than the average voucher recipient, when renting a unit above the payment standard.

These findings are a double-edged sword. On the one hand, HUD's programmatic income floor and ceiling have helped to keep housing costs for voucher recipients within a range that is consistent with programmatic goals. On the other hand, our analysis suggests that housing cost burdens rise after a household's initial lease has expired. HUD's ability to keep housing cost burdens in check is limited to some extent by the quality and frequency of local rent-reasonableness evaluations and the local payment standard provision, which places a cap on HUD's contribution toward rent. Some have suggested removing the 40-percent cost burden threshold altogether or eliminating rent reasonableness evaluations to enable households to incur higher housing costs if they so choose (Turnham and Khadduri, 2001). Our evidence suggests that without further changes to the HCV program and how it is administered by local PHAs, both the 40-percent threshold on total tenant contributions and the payment standard cap on HAPs will continue to play an important role in shaping housing cost burdens for HCV-assisted households.

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Authors

Casey Dawkins is the Director of the Urban Studies and Planning Program, the Director of the Ph.D. Program in Urban and Regional Planning and Design, associate professor of urban studies and planning, and affiliate of the National Center for Smart Growth at the School of Architecture, Planning and Preservation at the University of Maryland.

Jae Sik Jeon is a housing research analyst at Sage Computing and affiliate of the National Center for Smart Growth at the University of Maryland.

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Opting In, Opting Out: A Decade Later

Anne Ray
University of Florida

Jeongseob Kim
Ulsan National Institute of Science and Technology

Diep Nguyen
Jongwon Choi
University of Florida

Kelly McElwain
Keely Jones Stater
Public and Affordable Housing Research Corporation

Abstract

This article updates the U.S. Department of Housing and Urban Development (HUD) report Multifamily Properties: Opting In, Opting Out and Remaining Affordable *(Finkel et al., 2006). The original report examined the loss of affordable housing associated with HUD's Section 8 project-based rental assistance and Section 236 and 221(d)(3) subsidized mortgage programs between 1998 and 2004. It found that properties with low rents compared to the surrounding Fair Market Rent (FMR), that serve a family population, and that are owned by for-profit corporations were particularly at risk for loss of affordability.*

The analysis is updated here for the period 2005 to 2014. It shows that more owners made active decisions to opt in to Section 8 assistance in the latter period, while HUD's older subsidized mortgage programs were largely being phased out. Factors such as for-profit ownership and low rent-to-FMR ratios continued to be associated with higher risk of loss of affordability, but these factors were less influential from 2005 to 2014 than in the original study.

The article also explores the use of the Low-Income Housing Tax Credit Program and HUD refinancing to preserve affordability in Section 8 developments. The analysis finds that these preservation tools are associated with extended affordability for thousands of HUD-assisted properties. Additional preservation initiatives and improved targeting may be needed to preserve other HUD-assisted properties, particularly smaller developments in strong real estate markets.

Introduction

U.S. Department of Housing and Urban Development (HUD) multifamily programs are a critical source of affordable housing. As of 2016, these programs provided over 1.4 million assisted housing units: privately owned rental units whose owners receive subsidized mortgages, rent subsidies, or both in exchange for making these units affordable to low-income households through tenant income and rent restrictions. Affordable housing options provided by these programs serve a particularly vulnerable population. Three-fourths of developments funded through HUD's multifamily programs serve extremely low-income households (under 30 percent of area median income). More than one-half serve elderly households (HUD, 2016).

The affordability of the assisted housing stock faces risk from two directions. First, tenant income and rent restrictions placed on properties are time-limited. When restrictions expire, owners of developments in strong real estate markets can opt out of subsidy programs and convert properties to market-rate rental units, condominiums, or other uses. Second, the HUD-assisted housing stock dates to the 1960s through 1980s. Many aging properties are at risk of loss because of foreclosure or abatement of rental assistance contracts due to poor physical conditions.

Pinpointing the properties that are most at risk of loss enables affordable housing developers, advocates, and funders to intervene early to preserve affordability and allow these properties to continue to serve low-income households. Preservation of assisted properties usually calls for new subsidized financing to rehabilitate aging facilities and extend affordability requirements. It often also includes transferring properties to owners whose mission is to provide affordable housing to low-income tenants over the long term.

Original Study

To help the affordable housing community develop early warning systems for at-risk properties, in 2006 HUD published *Multifamily Properties: Opting In, Opting Out and Remaining Affordable* (Finkel et al., 2006). The study assessed the loss of HUD-assisted multifamily units over the 1998-to-2004 period. The study included properties subsidized by HUD's 1960s- to 1970s-era Section 221(d)(3) and Section 236 programs, which provided low-interest mortgages to housing owners, and HUD's 1970s- to 1980s-era project-based Section 8 program, through which HUD offered ongoing assistance to subsidize rents of low-income tenants. In all, the study covered 22,471 rental developments across the country (Finkel et al., 2006).

The 1998-to-2004 period was a risky time for the HUD-assisted inventory because developments funded in the 1960s and 1970s had passed the 20-year mark. Although subsidized mortgages typically carried a 40-year term, most were eligible for prepayment after the first 20 years. If an owner prepaid a mortgage, rent and income restrictions on the property were extinguished. Similarly, owners could choose not to renew Section 8 rental assistance contracts after their initial term expired, also usually 20 years. This would also end income and rent restrictions.

Finkel et al. (2006) tracked losses to the affordable housing inventory from prepayments, contract opt-outs, foreclosures, and contract abatements due to poor conditions. It found that 4,100 properties with 303,638 affordable units were lost between 1998 and 2004, amounting to 19 percent of the inventory. At the same time, owners of 11,126 properties with 785,143 units made active decisions to renew rental assistance contracts (Finkel et al., 2006). Most of the rest of the properties did not require active decisions during the study period, such as developments whose Section 8 contracts were not due to expire until after 2004.

The authors used descriptive cross-tabulations and multivariate analysis to identify the property characteristics associated with heightened risk of loss of affordability. The analysis identified the following characteristics associated with higher risk of property loss: smaller properties, low rents compared to the surrounding Fair Market Rent (FMR), funding from HUD's early assistance programs, family occupancy, and for-profit ownership. Conversely, properties with nonprofit ownership, higher rents compared to the surrounding FMR, and elderly and disabled occupancy type were at lower risk of loss (Finkel et al., 2006).

Updated Analysis

This study replicates the Finkel et al. (2006) analysis for a new time period, 2005 to 2014. It addresses two research questions—

1. Do basic characteristics such as location, ownership, physical attributes, and neighborhood characteristics explain differences in the prevalence of opt-outs/prepayments and opt-ins?
2. How have the patterns and trends in opt-outs and prepayments changed since the initial study took place?

To answer these questions, we assessed the status of over 18,000 properties that remained in HUD's multifamily portfolio following Finkel et al. (2006). A baseline dataset of these properties from 2005 was compared to the 2014 inventory to determine whether properties have continued to operate as affordable housing. As in the original study, properties that exited the affordable inventory were classified based on whether they exited through an owner's choice not to renew Section 8 contracts (*opt-out*), prepayment or maturing of subsidized mortgages, HUD foreclosure and contract abatement actions, or a combination of these. For properties that continued to operate in the assisted inventory, we determined whether the owner made an active choice during the study period to renew assistance (*opt-in*).

This article begins with a discussion of the data and methods used to classify the properties into opt-in, opt-out/prepay, and foreclosure/abatement outcome categories and to update the quantitative analyses. Next, the article provides the results of the cross-tabulations of outcomes by property characteristics and the multivariate analysis of the effects of selected characteristics on the owners' opt-in/opt-out decisions.

Finally, we present additional analysis exploring preservation interventions among properties with an active Section 8 opt-in. The infrastructure for preserving at-risk assisted housing emerged during the 1990s and continued to mature during the study periods for both Opting In, Opting Out analyses. This article takes a first step toward tracking the effects of these initiatives by identifying properties with financial transactions potentially related to preservation, including Low-Income Housing Tax Credit Program (LIHTC) allocations, HUD's Mark-to-Market process, and HUD-insured refinancing. The article also examines the extent to which preservation tools have been targeted toward properties that are particularly at risk of opt-out.

Data and Methods

The new analysis mirrors the 2006 study's methods and data sources for classifying properties by opt-in/opt-out/foreclosure-abatement status, cross-tabulating property characteristics with subsidy outcomes, and multivariate analysis of the opt-in/opt-out decision.

Active properties from 2005 were included if they had funding from at least one of these HUD programs, classified as "older" or "newer" assistance programs in the original study (Finkel et al., 2006)—

- Older (1960s to 1970s): Rent Supplement (Rent Supp), Rental Assistance Payment (RAP), and Loan Management Set-Aside (LMSA) rental assistance programs; Section 221(d)(3) Below Market Interest Rate (BMIR) and Section 236 Mortgage Assistance Program subsidized mortgages.
- Newer (1970s to 1980s): Section 8 New Construction/Substantial Rehabilitation (NC/SR) and Section 8 Moderate Rehabilitation (Mod Rehab).[1]

For brevity, all the types of rental assistance listed previously, including the older Rent Supp and RAP programs, are hereafter referred to as "Section 8." The mortgage programs hereafter are referred to together as "236/BMIR."

Classifying Properties by Outcomes

HUD provided point-in-time property-level datasets for 2005 and 2014, listing all developments with active subsidies from Section 8, 236/BMIR, or both. The study universe was made up of properties in the HUD inventory in 2005: 18,107 developments with 1.49 million housing units. We compared the two datasets to determine whether each property continued as subsidized housing (*stayers*) or left the subsidized inventory between 2005 and 2014 (*leavers*). Properties were placed in four categories based on their reasons for staying or leaving the subsidized housing inventory—

1. *Opt-in* refers to stayers where the owner actively renewed a Section 8 contract during the study period. Most of these properties had no 236/BMIR mortgage. Some had mortgages that were still active or had matured by 2014.
2. *Opt-out* refers to leavers with a Section 8 opt-out, 236/BMIR prepayment or both. Properties with both types of assistance were included if the owner actively terminated both subsidies or if the property had a Section 8 opt-out and a maturing mortgage.
3. *Foreclosure/abatement* refers to leavers where HUD abated a Section 8 contract due to property conditions, foreclosed on a 236/BMIR mortgage, or both. A small number of stayers that were still undergoing the contract abatement process in 2014 were also included.

[1] The original study noted that, "(t)he Office of Public and Indian Housing manages most projects assisted with Section 8 moderate rehabilitation. These projects are not included in the Real Estate Management System (REMS) or a comparable database. The REMS database only includes the subset of such projects that are also associated with the Section 8 Property Disposition program. Consequently, our analysis of the Section 8 Moderate Rehabilitation projects in this study is limited to this part of the stock" (Finkel et al., 2006: 3). The same constraint applies to the updated version.

4. The *Other* category covers both stayers and leavers without a clear opt-in, opt-out or foreclosure and abatement action. Most were stayers where the owner did not have to make a Section 8 renewal choice because the Section 8 contract term continued through the entire 2005-to-2014 period. It also includes stayers where the owner made a mixed decision to continue one type of assistance but not the other. Most notably, owners of hundreds of properties prepaid 236/BMIR mortgages from 2005 through 2014 but continued to have active Section 8 assistance. The category also includes a small number of leavers where 236/BMIR mortgages were terminated for reasons other than prepayment, maturity or foreclosure.

Property Characteristics for Descriptive Cross-Tabulations

As in the original study, properties in the four outcome categories were cross-tabulated with a series of property, financing, owner, location, and tenant characteristics. Exhibit 1 shows the data sources for each characteristic. Unless otherwise noted, properties were classified based on their characteristics during the 2005 baseline year.

Exhibit 1

Data Sources for Property Characteristics

Variables	Data Source
Property geocoding (census tract, MSA, census division, metropolitan location)	Generated from HUD iREMS
Property characteristics (size, occupancy type, building type, percent assisted, building age based on occupancy date, REAC score)	2005 active properties, multifamily building type (generated from HUD iREMS)
Units by number of bedrooms	2005 active properties
HUD program type: older assisted versus newer assisted	2005 active properties
Detailed financing information (financed by FHA insurance, Section 202, Section 811, USDA Section 515, state HFAs)	HUD 2005 and 2014 active properties, active financing, active contracts, and multifamily building type files, iREMS; terminated contracts database; terminated multifamily mortgages database
Ownership type	2005 active participants database (generated from HUD iREMS)
Neighborhood characteristics (median household income, median gross rent, median value of owner-occupied housing, homeownership rate, poverty rate, homeowner and renter vacancy rate, racial/ethnic composition)	U.S. Census Bureau, 2005–2009 American Community Survey. Summary files constructed by Minnesota Population Center. National Historical Geographic Information System: Version 2.0.
Home sales market (change in Housing Price Index)	Federal Housing Finance Agency Housing Price Index
Rental market (change in HUD FMR)	HUD annual FMR datasets, 2005–2014
Tenant characteristics (length of residence, household size, percent minority headed, percent elderly, percent with children, household income as percentage of AMI)	HUD Picture of Subsidized Households, 2005

AMI = Area Median Income. FHA = Federal Housing Administration. FMR = Fair Market Rent. HFA = housing finance agency. HUD = U.S. Department of Housing and Urban Development. iREMS = Integrated Real Estate Management System. MSA = metropolitan statistical area. REAC = Real Estate Assessment Center. USDA = U.S. Department of Agriculture.

Multivariate Analysis

Both studies include a logistic regression model to isolate the effects of property, financing, and location characteristics on owners' decisions to opt into or out of Section 8 assistance. As noted in the original report (Finkel et al., 2006), multivariate analysis adds depth to the initial findings of the descriptive statistics. The model isolates the influence of each variable on the opt-in/opt-out decision. The apparent relationships between some variables and property outcomes in the descriptive cross-tabulations may drop out when the other factors are controlled.

The original analysis included the Section 8 only properties where the owner had to make an explicit decision to renew or opt out of a contract from 1998 to 2004. The new version widens this universe slightly by adding the small group of Section 8 and 236/BMIR properties where the owner made at least one opt-in/opt-out choice during the 2005-to-2014 study period. Properties were excluded if they did not have Section 8 assistance, if their Section 8 contracts did not come up for renewal between 2005 and 2014, or if data were insufficient to evaluate all variables. In all, the multivariate analysis covers 10,023 properties.

Results

In this section, we report the results of the classification of properties by HUD funding program and outcome, the descriptive cross-tabulations, and the multivariate analysis. We find that many of the same factors associated with the loss of affordable properties from the earlier study period continued to apply but that these patterns were less pronounced in the 2005-to-2014 period.

Stayers and Leavers

The analysis shows that property losses had slowed considerably since the Finkel et al. (2006) study period. Only 8 percent of properties were lost from 2005 to 2014, compared to 19 percent of properties in the original study. Exhibit 2 shows the change in the number of properties with each combination of Section 8 and 236/BMIR subsidy. Exhibit 3 shows the breakdown of properties by the four outcome categories: opt-in, opt-out/prepay, foreclosure/abatement, and the miscellaneous Other category.

Exhibit 2

Property Inventory Changes by Subsidy Type, 2005–2014

Subsidy Type	Remained in 2014 Inventory		Left Inventory by 2014		Leavers as Percent of Subsidy Type, Finkel et al. (2006)
	Number	Percent of Subsidy Type	Number	Percent of Subsidy Type	
Section 8 only	14,543	95	737	5	9
236/BMIR only	79	15	443	85	82
Section 8 and 236/BMIR	2,033	88	272	12	32
Total	16,655	92	1,452	8	19

236/BMIR = Section 236 Mortgage Assistance Program and Section 221(d)(3) Below Market Interest Rate Program.
Sources: U.S. Department of Housing and Urban Development, 2005 and 2014 active properties and active financing files, Integrated Real Estate Management System; Finkel et al. (2006)

Exhibit 3

Properties by Summary Outcome Categories, 2005–2014

	Opt-Ins	Opt-Outs/ Prepays	Foreclosure/ Abatement	Other	Total
Number of properties	12,786	748	293	4,280	18,107
Percent of properties	71	4	2	24	100

Sources: U.S. Department of Housing and Urban Development, 2005 and 2014 active properties, active financing, and active contracts files, Integrated Real Estate Management System; terminated contracts database; terminated multifamily mortgages database

- **Section 8 only.** In the original report, the most common outcome (68 percent of cases) was continued affordability in a Section 8 only property, either through an opt-in contract renewal or a *no choice* continuation of an existing contract. This pattern was even stronger in the new analysis; 80 percent of the study dataset was made up of Section 8 only properties where either the owner renewed a contract between 2005 and 2014 or the contract extended throughout the entire period. Fewer than 4 percent of the Section 8 only properties left the inventory during the study period. Most did so through owner opt-outs, with a smaller number of HUD-abated contracts.

- **Section 236/BMIR only.** Within the small stock of 236/BMIR properties without Section 8 that remained in 2005, most left the subsidized inventory through mortgage maturity, prepayment, or another termination reason by 2014.

- **Section 8 and 236/BMIR.** For properties with both types of assistance, the most common outcome was a Section 8 opt-in combined with an end to the 236/BMIR mortgage through prepayment, maturity, or other termination reasons. Surprisingly, Section 8 opt-outs upon mortgage termination did not appear to be a threat to the inventory. Owners of properties with prepaid or maturing mortgages opted out of Section 8 assistance in only 112 cases, comprising 9 percent of Section 8 properties with prepaid or maturing mortgages.

Overall, the 2005-to-2014 analysis reflects two trends: the continuation of most Section 8 assistance and the winding down of subsidized mortgage programs.

Descriptive Cross-Tabulations

Exhibit 4 shows the cross-tabulations of properties in the four subsidy outcome categories by property, tenant, financing, and location characteristics.[2]

The original report emphasized the loss of affordability in properties with family occupancy type, low rent-to-FMR ratios, and for-profit ownership. These patterns were also present in the 2005-to-2014 cross-tabulations.

First, housing for families was particularly at risk. Properties with family occupancy type made up 75 percent of opt-outs and 70 percent of foreclosure/abatements, even though they only made up 48 percent of the total property inventory. Single-parent households with children were

[2] Ray et al. (2015) included a more extensive discussion of the rules for classifying properties by outcome, a table showing properties by detailed combinations of Section 8 and 236/BMIR outcomes, and a more detailed discussion of the descriptive cross-tabulation results.

Exhibit 4

Property, Financing, Location, and Tenant Characteristics by Outcome (1 of 3)

	Opt-Ins	Opt-Outs/ Prepays	Foreclosure/ Abatement	All Other	Total
Property characteristics					
Number of properties	12,786	748	293	4,280	18,107
Percent of properties	71	4	2	24	100
Development size					
1–49 (%)	44	46	51	28	40
50–99 (%)	27	23	22	32	28
100–199 (%)	23	22	18	30	25
200 or more (%)	6	8	9	10	7
Average number of units	77	79	81	98	82
Unit size					
0 bedrooms (%)	7	5	4	5	7
1 bedrooms (%)	55	37	29	46	52
2 bedrooms (%)	25	43	43	31	27
3 bedrooms (%)	11	14	20	15	12
4+ bedrooms (%)	2	1	3	2	2
Average number of bedrooms	1.6	1.8	2	1.7	1.6
Occupancy type (%)					
Elderly/disabled	59	25	30	38	52
Family	41	75	70	62	48
Building type (%)					
Rowhouse	10	6	8	8	9
Townhouse	3	5	2	4	3
Semidetached	5	3	3	4	5
Detached	5	4	7	1	4
Walkup/garden	36	56	55	37	37
Midrise	3	1	2	3	3
Mixed	12	13	15	18	14
Highrise/elevator	28	11	9	25	26
Categories of rent-to-FMR ratio (%)					
Below 80%	11	28	21	16	13
80–100%	24	37	41	30	26
101–120%	27	20	22	30	27
121–130%	11	6	5	8	10
131–40%	8	3	5	6	7
141–160%	10	4	2	6	9
Over 160%	9	3	3	4	7
Building-age categories (%)					
Before 1975	17	38	33	30	21
1975–1979	20	19	21	30	22
1980–1985	46	35	31	37	43
After 1985	17	8	15	3	13
Ownership type[a] (%)					
Nonprofit	49	25	36	26	43
For profit	33	40	32	39	35
Limited dividend	15	27	28	30	19
Other	2	8	4	4	3
REAC Physical Inspection Score (1–100)					
Median	91	88	79	89	90
1–59 (%)	2	5	24	4	3
60–69 (%)	6	9	12	6	6
70–89 (%)	36	42	36	41	37
90–100 (%)	56	44	28	50	54

Exhibit 4

Property, Financing, Location, and Tenant Characteristics by Outcome (2 of 3)

	Opt-Ins	Opt-Outs/ Prepays	Foreclosure/ Abatement	All Other	Total
Financing characteristics					
Newer (Section 8 NC/SR, Mod Rehab) (%)	80	57	55	58	73
Older (Rent Supp/RAP, LMSA, 236/BMIR) (%)	20	43	45	42	27
Detailed HUD program type (%)					
Sec. 8 NC/SR	25	25	16	25	25
Sec. 202	29	4	15	3	21
Sec. 8/LMSA	19	25	41	25	21
Sec. 8/515	10	7	8	2	8
Sec. 8/HFDA	12	11	7	27	15
Sec. 8/Preservation	2	3	1	2	2
Sec. 8/PD	3	10	9	1	3
Rent Supp/RAP	1	0	0	6	2
No Rental Subsidy	0	16	4	9	3
Average percentage of assisted units	94	60	82	83	90
Primary form of financing (%)					
FHA insured	27	39	23	51	33
Section 202/811	27	4	12	2	20
Section 515	10	7	8	2	8
All other	36	51	57	45	39
HFA-related properties					
Number of HFA-related properties	1,553	82	21	1,140	2,796
Percent of HFA-related properties	56	3	1	41	100
FHA insured (%)	24	21	19	24	24
Noninsured (%)	76	79	81	76	76
Location and market characteristics					
Census division (%)					
New England	10	4	3	14	10
Mid Atlantic	13	10	9	15	13
East North Central	18	12	20	20	18
West North Central	11	19	16	11	11
South Atlantic	16	16	22	14	15
East South Central	7	6	8	9	8
West South Central	7	10	15	6	7
Mountain	5	7	3	5	5
Pacific	13	16	4	8	12
Metropolitan location (%)					
Suburb	31	28	22	33	31
Principal city	51	60	61	53	52
Nonmetropolitan	18	12	18	15	17
Neighborhood characteristics (averages for census tracts surrounding properties)					
Median household income ($)	39,831	41,937	35,371	38,363	39,498
Median gross rent ($)	693	741	652	675	690
Median value of owner-occupied housing ($)	197,022	200,939	146,169	191,037	194,958
Homeownership rate (%)	52	51	51	50	52

Exhibit 4

Property, Financing, Location, and Tenant Characteristics by Outcome (3 of 3)

	Opt-Ins	Opt-Outs/ Prepays	Foreclosure/ Abatement	All Other	Total
Poverty rate (%)	22	20	26	23	22
Homeowner vacancy rate (%)	3	3	4	4	3
Renter vacancy rate (%)	7	8	10	8	8
Racial/ethnic composition (%)					
White	60	59	48	58	59
African American	19	19	36	22	20
Hispanic	15	15	11	14	15
Asian	3	3	2	3	3
Other	3	3	3	3	3
Minority	40	41	52	42	41
Regional housing market (averages for MSAs or non-MSA state values surrounding property)					
Home sales market					
Average percent change in HPI, full study period (2005 Q1–2014 Q1)	3	6	5	1	3
Average percent change in HPI, strong market period (2005 Q1–2007 Q1)	14	16	14	12	14
Average percent change in HPI, weak market period (2007 Q1–2012 Q1)	– 13	– 14	– 11	– 13	– 13
Average percent change in HPI, recovering market period (2012 Q1–2014 Q1)	6	8	4	6	6
Rental market					
Average percent change in FMR, 2005–2014	27	27	29	26	27
Average tenant characteristics					
Length of residence (years)	5.9	5.9	5.2	5.8	5.9
Household size (people)	1.6	1.9	2.1	1.9	1.7
Percent minority headed	40	46	66	45	41
Percent of all persons with disability	22	17	17	16	20
Percent elderly headed	49	30	20	39	46
Percent with 2+ adults and children	5	9	8	8	6
Percent with 1 adult and children	20	30	41	28	22
Household income as a percentage of AMI	23	22	17	22	22

236/BMIR = Section 236 Mortgage Assistance Program and Section 221(d)(3) Below Market Interest Rate Program. AMI = Area Median Income. FHA = Federal Housing Administration. FMR = Fair Market Rent. HFA = housing finance agency. HFDA = Housing Finance and Development Agency. HPI = Housing Price Index. LMSA = Loan Management Set-Aside program. Mod Rehab = Section 8 Moderate Rehabilitation program. MSA = metropolitan statistical area. NC/SR = New Construction/Substantial Rehabilitation program. PD = Property Disposition. Q1 = first quarter. RAP = Rental Assistance Payment program. REAC = Real Estate Assessment Center. Rent Supp = Rent Supplement program.

[a] Ownership type was missing for 15 percent of properties. Percentages refer to set of properties for which owner type was known.

Sources: U.S. Department of Housing and Urban Development, 2005 and 2014 active properties, active financing, active contracts, and multifamily building type files, Integrated Real Estate Management System; terminated contracts database; terminated multifamily mortgages database; 2005 and 2014 FMRs; U.S. Census Bureau, 2005–2009 American Community Survey; Federal Housing Finance Agency HPI; 2005 Picture of Subsidized Households disproportionately present in the opt-out category and, in particular, foreclosure/abatement properties. Conversely, properties with elderly or disabled occupancy type made up over half of total properties, but only 25 to 30 percent of opt-outs and foreclosure/abatement properties.

Second, properties with rents below those of the regional market continued to be overrepresented among opt-outs. This is represented by the rent-FMR ratio. The numerator of this ratio is the rent that the property owner receives each month from HUD and the tenant; the denominator is the HUD FMR for the surrounding metropolitan area or county. Owners receiving below-market rents have a greater incentive to opt out, because they are more likely to be able to command higher rents from unsubsidized tenants. Only 13 percent of all properties in the study had rent-FMR ratios below 80 percent, but they represented 28 percent of all opt-outs. Properties with rents at 80 to 100 percent of FMR made up 26 percent of the total inventory but 37 percent of opt-outs.

Properties owned by for-profit and limited dividend corporations continued to be at higher risk of opt-out. Nevertheless, the 2005-to-2014 analysis shows some shift in opt-outs to nonprofits. Nonprofit owned properties made up 25 percent of opt-outs in the 2005-to-2014 study, compared to only 9 percent in the earlier study.

Unsurprisingly, properties in neighborhoods with stronger markets were more prone to opt-outs, whereas those in weaker markets were more prone to foreclosure/abatement. Among opt-out properties, census tract-level median household income, median rent, and home values were higher, but the poverty rate was lower. For the foreclosure/abatement properties, these patterns were reversed. Also unsurprisingly, foreclosures and abatements were more common among the oldest properties (pre-1975) and those with failing physical inspection scores from HUD's Real Estate Assessment Center (REAC).

In summary, the descriptive analysis showed that fewer properties left the assisted housing inventory from 2005 to 2014 compared to the original 1998-to-2004 study period. To the extent they did occur, opt-outs continued to disproportionately affect developments with rents below the regional FMR and in strong neighborhood markets. Opt-outs were also more common in properties with for-profit or limited dividend owners, although nonprofit-owned properties made up a larger share of opt-outs than in the original study. For their part, properties in weak neighborhood markets and with failing physical inspection scores were disproportionately affected by foreclosures and contract abatements. Finally, family-occupied properties continued to face higher risk from both opt-outs and foreclosures/abatements than developments with elderly and disabled occupancy.

Multivariate Analysis

The second type of quantitative analysis in the original study was a logistic regression model to isolate the effects of property, financing, and location characteristics on owners' decisions to opt into or out of Section 8 assistance. The independent variables were potential opt-out risk factors; the dependent variable was the decision to opt out of a Section 8 contract during the study period.

In the earlier study, the multivariate analysis identified these variables as key factors that increased opt-out risk: rent-FMR ratio below 80 percent, properties with all units receiving Section 8 assistance, for-profit/limited dividend ownership, family occupancy, property size below 50 units, and concentrations of units with fewer than three bedrooms (Finkel et al, 2006).

The updated model includes all independent variables from the original study plus variables related to REAC scores, census tract minority and homeownership rates, and neighborhood and metropolitan housing market indicators. It also includes the presence of a maturing 236/BMIR mortgage as a potential opt-out risk factor, a variable that would not have been relevant during the previous study period.

Exhibit 5 shows the variables included in the updated analysis. The rightmost column describes the anticipated direction for each variable. For variables repeated in both study periods, this is a description of the results from the previous analysis. For new variables, we suggest an expected direction.

Exhibit 5

Variables for Regression Model (1 of 3)

Variable Type	Variable	Categories	Original Results or Expected Direction
Property	Property size (units)	Less than 50 units (ref.) 50–99 units 100–199 units 200+ units	Original study: Reduced odds of opt-out as project size increases.
	Density	Percent of units with 3 or more bedrooms	Original study: Reduced odds of opt-out as number of larger units increases.
	Occupancy type	Family Elderly/disabled (ref.)	Original study: Increased odds of opt-out in family properties
	Building type	Detached/semidetached Other types (ref.)	Original study: Slightly increased odds of opt-out in detached/semidetached.
	Ownership type	Nonprofit For-profit/limited dividend (ref.)	Original study: Increased odds of opt-out for for-profit-owned properties.
	REAC	Physical REAC score (1-point increase)	Expected direction: Unknown. Higher REAC score may increase odds of opt-out because properties in good physical condition are more marketable to market-rate tenants. However, owners of properties in poor condition could opt out of subsidy programs to preempt a HUD decision to abate subsidies.
	Ratio of rent-to-FMR	Less than 80% 80–99.9% 100–119.9% (ref.) 120–129.9% 130–139.9% 140–159.9% 160% or more	Original study: Strongly increased odds of opt-out for properties with lower rent-to-FMR ratios, particularly less than 80 percent.

Exhibit 5

Variables for Regression Model (2 of 3)

Variable Type	Variable	Categories	Original Results or Expected Direction
Financing	Older assisted HUD programs	Older assisted = 1 Newer assisted = 0	Original study: Increased odds of opt-out for older assisted properties.
	100-percent assisted[a]	Projects with 100 percent of units with rental assistance = 1 Other = 0	Original study: Strongly increased odds of opt-out for 100-percent assisted properties.
	FHA insured	FHA insured =1 Other = 0	Expected direction: Lower odds of opt-outs for properties with insured mortgages because some FHA mortgages impose affordability restrictions.
	HFA related	HFA related =1 Other = 0	Unknown: Original results were not statistically significant.
	Mortgage matured	Matured mortgage of 236/ BMIR properties = 1 Other = 0	Expected direction: Higher odds of opt-out for properties with maturing mortgages, because restrictions associated with the mortgage are ending.
Neighborhood	Poverty rate	Percent of persons below poverty level in a census tract	Original results: Lower odds of opt-out for properties in neighborhoods with higher poverty rate.
	Minority rate	Percent of minority (All races except non-Hispanic White) in a census tract	Expected direction: Lower odds of opt-out because of difficulty marketing developments in racially segregated areas.
	Homeownership rate	Percent of owner-occupied housing in a census tract	Expected direction: Unknown. Higher homeownership rate may signal an overall stronger neighborhood housing market but also may imply a smaller surrounding renter population, making it more difficult to attract tenants.
Location	Metropolitan location	Suburbs (ref.) Principal cities Nonmetropolitan	Original study: Increased odds of opt-out for central city and nonmetropolitan locations
	Census division	New England Mid Atlantic East North Central West North Central South Atlantic (ref.) East South Central West South Central Mountain Pacific	Original study: Increased odds of opt-out for Mid Atlantic, East North Central, West North Central, West South Central, Mountain and Pacific regions; decreased odds for New England and East South Central.

Exhibit 5

Variables for Regression Model (3 of 3)

Variable Type	Variable	Categories	Original Results or Expected Direction
Housing market	Neighborhood rent level	Ratio of median gross rent between a census tract and a county	Expected direction: Increased odds of opt-out for properties in neighborhoods with a high tract rent-county rent ratio.
	Neighborhood housing value	Ratio of median value of owner-occupied housing between a census tract and a county	Expected direction: Increased odds of opt-out for properties in neighborhoods with a high tract value-county value ratio.
	Regional sale market	Percent change in HPI 2007 Q1–2012 Q1 25% or more 0–24.99% – 25%~ 0.01% (ref.) – 50%~ – 25.01% Lower than – 50%	Expected direction: Increased odds of opt-out for properties in neighborhoods with positive change in HPI.
	Regional rental market	Percent change in FMR during the recession, 2007 Q1–2012 Q1 20% or more 10%–19.99% 0%–9.99% Less than 0% (ref.)	Expected direction: Increased odds of opt-out for properties in neighborhoods with higher positive change in FMR.

236/BMIR = Section 236 Mortgage Assistance Program and Section 221(d)(3) Below Market Interest Rate Program. FHA = Federal Housing Administration. FMR = Fair Market Rent. HFA = housing finance agency. HPI = Housing Price Index. HUD = U.S. Department of Housing and Urban Development. Q1 = first quarter. REAC = Real Estate Assessment Center. ref. = reference category.

[a] Developments were classified as 100-percent assisted if total units exceeded assisted units by no more than two. The two-unit difference was allowed to account for developments where one or two units are used as management offices.

Exhibit 6 shows the results of the logistic regression model. The odds ratios refer to the odds that an owner will opt out of a Section 8 contract with that particular characteristic. For categorical variables (for example, property size), the odds ratios refer to the characteristics in comparison to the reference group. For continuous variables, the odds ratios show the direction of increase or decrease in odds of opt-out given a positive change in the indicator.

Family properties continued to be at higher risk in the 2005-to-2014 study period. Odds of opt-out for family properties were approximately double those of properties restricted to elderly/disabled tenancy, similar to the results in the original study.

Smaller properties and units also continued to be at higher risk of loss. Properties with fewer than 50 units had a two- to four-times higher risk of opt-out than larger properties. Similarly, as the share of units with three or more bedrooms in a property increased, its risk of opt-out decreased, indicating that properties offering more studio and one- or two-bedroom units were at increased opt-out risk. Both of these results are consistent with the original study.

Two other key risk factors continued to affect opt-outs from 2005 to 2014, but they played a smaller role than in the original study. First, low rent-to-FMR ratios continued to be a risk factor. Odds of opt-out for properties with rent-to-FMR below 80 percent from 2005 to 2014 were three

Exhibit 6

Odds Ratios for Opt-Out Decision Model, 2005–2014

	Variable	Odds Ratio	*p*-value
Property size (ref. under 50 units)	Property size 50–99	0.388	***
	Property size 100–199	0.339	***
	Property size 200+	0.232	***
Density	Percent of units with 3 or more bedrooms	0.332	***
Occupancy types	Family (ref. elderly/disabled)	2.207	***
Building types	Detached or semidetached (ref. other)	1.044	
Ownership types	Nonprofit (ref. for-profit/limited dividend)	0.472	***
REAC physical score	1-percentage-point increase	0.982	***
Program	Older assisted (ref. newer assisted)	0.552	***
	100% assisted units (ref. partially assisted)	0.132	***
	FHA insured	0.432	*
	HFA related	1.999	**
	Matured 236/BMIR mortgage	1.016	
Neighborhood	Poverty rate	0.356	
	Minority rate	0.869	
	Homeownership rate	0.359	**
Rent-to-FMR ratio (ref. 100–119.9%)	Less than 80%	2.990	***
	80–99.9%	1.885	***
	120–129.9%	0.730	
	130–139.9%	0.455	**
	140–159.9%	0.564	*
	160% or more	0.512	*
Metropolitan location (ref. suburbs)	Principal cities	1.213	
	Nonmetropolitan	1.088	
Census division (ref. South Atlantic)	New England	0.363	***
	Mid Atlantic	0.827	
	East North Central	0.612	**
	West North Central	1.233	
	East South Central	0.790	
	West South Central	0.780	
	Mountain	1.879	**
	Pacific	0.853	
Neighborhood market	Neighborhood rent/county ratio	4.036	***
	Neighborhood housing value	1.365	**
Regional sale market (2007–2012) (ref. moderate decline; – 25% to 0% change)	Severe decline: – 50% or more	0.929	
	Decline: – 25% to – 50 %	0.942	
	Growing: 0–25%	1.634	***
	Strongly growing: 25% or more	1.483	
Regional rental market (2007–2012) (ref. FMR declining)	Stable: 0–10%	1.385	
	Growing: 10–20%	1.197	
		1.218	
Total number of properties		10,023	
Opt-outs		361	
Pseudo R^2		0.2101	

236/BMIR = Section 236 Mortgage Assistance Program and Section 221(d)(3) Below Market Interest Rate Program. FHA = Federal Housing Administration. FMR = Fair Market Rent. HFA = housing finance agency. REAC = Real Estate Assessment Center. ref. = reference category.

*** $p < 0.01$. ** $p < 0.05$. * $p < 0.10$.

Sources: U.S. Department of Housing and Urban Development, 2005 and 2014 active properties, active financing, active contracts, and multifamily building type files, Integrated Real Estate Management System; terminated contracts database; terminated multifamily mortgages database; 2005 Picture of Subsidized Households*; 2005 and 2014 FMRs; U.S. Census Bureau, 2005–2009 American Community Survey; Federal Housing Finance Agency Housing Price Index* times those of the 100-to-120 percent of FMR reference case. In the original study, odds of opt-out among properties with rent-to-FMR below 80 percent were nearly 12 times higher than the reference case. Second, properties owned by profit motivated companies continued to be at higher risk. Odds of opt-out for for-profit/limited dividend owned properties from 2005 to 2014 were double those for nonprofit owned properties (compared to a factor of six in the original study). These results suggest that the opportunity for higher rents in the private market continued to play a role in pushing profit-motivated owners of properties with below-market rents to opt out of subsidies, but not to the same degree as in earlier years.

For another key variable, the 2005-to-2014 results differed from the regression analysis in the original study. The original study showed that properties with rental assistance in all units were nearly 14 times more likely to opt out than those with partial Section 8 assistance. In the current analysis, however, fully assisted properties were seven to eight times less likely to opt out than partially assisted properties.

Financing characteristics also had significant effects that differed from the original study. Properties operating under HUD's older assisted programs (see the Data and Methods section) were only one-half as likely to opt out as those funded under newer HUD programs. Properties financed by state housing finance agencies (HFAs) were more likely to opt out than other properties. In contrast, the original study showed that older assisted properties were more likely to opt out and showed no statistically significant effect from HFA financing (Finkel et al., 2006). A possible explanation for the current results is that that the newer assisted properties and the state-financed properties were more likely to be reaching their first opt-out decision during the 2005-to-2014 study period, whereas the older assisted and non-state-financed properties would have actively opted in to Section 8 assistance at least once before 2005. We speculate that owners of properties are more likely to take their first opportunity to opt out rather than to renew a contract initially and subsequently opt out.

We added several variables to the model for the new study. Most of these related to neighborhood and regional market conditions. Opt-out risk was significantly higher for properties in strong neighborhood housing markets, signified by higher ratios of neighborhood (census tract) rents and housing values compared to the surrounding county. On the other hand, although a high homeownership rate might be expected to signal a strong neighborhood housing market, opt-outs were actually less likely in neighborhoods with higher homeownership rates. The lack of an active rental market in heavily owner-occupied neighborhoods may discourage market-rate conversion of properties. At the regional market level, properties in regions where home prices were moderately increasing from 2007 to 2012 were at higher risk of opt-out. Regional rental market changes, measured by changes in the HUD FMR over the same period, did not have a significant effect.[3]

[3] To account for the volatility in the overall housing market during the years under study, we also tested a model that segmented properties by the year of opt-in/opt-out decision into three periods: strong market (2005 to 2007), weak market (2008 to 2011), and recovering market (2012 to 2014). Surprisingly, results did not vary greatly across the three phases. Opt-outs were somewhat less likely among larger properties during the 2012-to-2014 recovering market phase, and during the weak market period the effect of family occupancy on opt-out risk was more pronounced. In general, however, results were consistent across the housing market time periods.

Two other newly added variables showed unanticipated results. First, we expected that Section 8 properties with a maturing 236/BMIR mortgage would be at higher risk of opt-out. The layer of affordability restrictions associated with the mortgage would be expiring. Absent other affordable financing layers, the owner would be free to convert the property to unrestricted rents upon opting out of the Section 8 contract. However, we found no significant effect from a 236/BMIR mortgage maturity.

Second, the risk associated with REAC physical inspection scores was difficult to predict. Higher inspection scores might be expected to increase the risk of opt-outs, as owners seek to convert the properties in the best physical condition to market-rate use. Instead, the model shows a 1-point increase in REAC score resulted in a *decrease* in odds of opt-out of approximately 1.6 percent. Owners of properties in poor physical condition may opt out of assistance preemptively if they expect HUD to abate a subsidy contract. Also, owners who are planning to opt out of subsidies and sell or convert properties to market-rate may delay investing in physical improvements until after the opt-out (Finkel et al., 2006).

In sum, the results confirm the original study's emphasis on the risk of loss for smaller properties and units and for developments serving families. The analysis also substantiates the emphasis on market factors at the property and in the surrounding community. Properties in neighborhoods with higher rents and home values were at heightened risk of opt-out, as were those with profit-motivated owners and rents below the surrounding FMR. However, owner type and rent-FMR ratio demonstrated considerably less influence on opt-outs during the 2005-to-2014 study period than in earlier years.

Preservation of Opt-In Properties

The opt-in/opt-out analysis showed considerably fewer losses in the Section 8-assisted inventory between 2005 and 2014 compared to the original 1998-to-2004 study period. Many of the properties most at risk of loss, either weak properties in financial and physical distress or strong properties with potential to attract market-rate tenants, likely left the assisted inventory during the earlier wave of opt-outs documented by the 1998-to-2004 analysis. The middle-of-the-road inventory that remained from 2005 to 2014 was more stable, particularly as an increasing number of owners had already been required to make one or more active decisions to renew subsidy contracts.

However, another reason that the 2005-to-2014 period may have generated fewer opt-outs is the maturing of the assisted housing preservation infrastructure. In the wake of well-publicized opt-outs in the 1990s, a variety of federal, state, local, and extra-governmental initiatives were put in place to preserve at-risk properties (HUD, 2013b).

- **HUD Mark-to-Market.** The Mark-to-Market program was put in place by the Multifamily Assisted Housing Reform and Affordability Act of 1997[4] to reduce above-market rents among HUD-financed properties with Section 8 assistance. The full restructuring option in Mark-to-Market provides restructured, favorable mortgage terms to owners of Section 8 developments

[4] Pub. L. 105–65. 111 Stat. 1344, October 27, 1997.

in exchange for reducing rents to market values. It acts as a preservation program in that participating owners agree to long-term affordability, typically through a 20-year Section 8 contract and a 30-year use agreement[5] (HUD, 2015, 2002).

- **Low-Income Housing Tax Credit Program allocations for preservation.** LIHTC can be used to finance the acquisition and rehabilitation of at-risk Section 8 properties by preservation-minded owners. According to the National Housing Trust, 45 states provide incentives for preservation through allocation of competitive (9-percent) tax credits, including 16 states with explicit set-asides for preservation (National Housing Trust, n.d.). States also devote private activity bonds and noncompetitive (4-percent) credits to preservation projects.

  Adding tax credits to an existing Section 8 development provides resources to improve financial and physical conditions at aging properties. LIHTC also imposes at least 30 years of tenant income and rent restrictions, which reduces the incentive for owners to opt out of Section 8 affordability provisions.

- **Federal Housing Administration (FHA)-insured mortgage refinancing.** A number of Section 8 properties have undergone refinancing through market-rate FHA-insured funding programs. These funding sources do not carry income or rent restrictions, so their presence does not necessarily signal a long-term commitment to affordability. Nevertheless, many recipients of these mortgages commit to long-term Section 8 contract renewals.

- **Preservation funding from state HFAs.** Many HFAs use affordable housing trust funds, grants and loan programs to provide additional predevelopment and gap financing for preservation of federally assisted units.

- **Preservation databases, including risk-targeting data.** A number of states and cities have launched property databases or improved existing data tools to flag properties at risk of loss to the affordable inventory.[6]

- **Additional state, local, and nongovernmental initiatives.** Beginning in 2001, the John D. and Catherine T. MacArthur Foundation's Window of Opportunity initiative underwrote tremendous growth in the rental preservation infrastructure, including support for capacity building among national and local nonprofit developers, building sources of private capital for preservation, local and state interagency preservation councils, legal assistance and organizing support for tenants, and policy advocacy and research (MacArthur Foundation, 2009).

[5] Mark-to-Market also offers a "Lite" option, which calls for reduction of rents without Federal Housing Administration mortgage restructuring. It is not included here as a preservation initiative because it only requires a 5-year renewal of Section 8 assistance and no long-term use agreement.

[6] See, for example, the Shimberg Center's Florida Assisted Housing Inventory at http://flhousingdata.shimberg.ufl.edu/AHI_introduction.html; CEDAC's database for Massachusetts at https://cedac.org/housing/housing-preservation; and the NYU Furman Center's Subsidized Housing Inventory Project at http://datasearch.furmancenter.org. The National Housing Preservation Database website includes a page of links to additional state and local preservation databases, at http://www.preservationdatabase.org/preservation-resources/local-partner-databases.

Preservation Transaction Types

In this analysis, we describe the presence of the first three financing tools—Mark-to-Market full restructuring, LIHTC allocations, and FHA mortgage refinancing—among the properties classified as Section 8 opt-ins in the 2005-to-2014 dataset. In addition, we explore the extent to which preservation resources are targeted toward at-risk properties. The potentially preserved properties are compared with other opt-in properties in terms of the risk factors identified in the multivariate analysis, such as family occupancy and rent-FMR ratios below 80 percent.

To determine whether the opt-in properties received these types of financing, the dataset of opt-in properties was matched to financing information from the National Housing Preservation Database (NHPD) and HUD's Mark-to-Market transactions database. Opt-in properties were considered to have a potential preservation transaction if the NHPD identified LIHTC as a funding source or HUD's database indicated the properties completed a Mark-to-Market full restructuring. A property also was considered to have a potential preservation transaction if the NHPD indicated FHA-insured refinancing *and* the property owner renewed the Section 8 contract for 19 to 20 years or longer during the 2005-to-2014 study period. We reasoned that the contract extension signaled a commitment to long-term affordability at the time the property was refinanced.[7]

In most cases, the preservation transactions took place during the 2005-to-2014 study period. Transactions were also included if they predated 2005, because earlier subsidies still could incentivize or require owners to opt in to the Section 8 program during the study period. Specifically, for LIHTC, 62 percent of properties had transactions between 2005 and 2014. Most of the rest received tax credits from 1997 to 2003. For HUD refinancing, 87 percent of properties had transactions between 2005 and 2014, with the remainder occurring from 1998 to 2004. For Mark-to-Market, 67 percent of properties closed on restructuring between 2005 and 2014, with the remainder occurring between 1999 and 2004.[8]

As a convenient shorthand, properties with at least one of these interventions are referred to as "preserved" in the following discussion, and the opt-ins without any of these interventions are referred to as "nonpreserved." In fact, *preservation* has no standard definition. Some of the preserved properties would have been unlikely to leave the inventory even without these additional interventions, and some of the nonpreserved properties may have undergone preservation interventions other than the three types tracked here. In particular, we are unable to track the use of grants and loans from state HFAs and local funders to preserve properties, because no single database tracks these funding sources for the national Section 8 inventory.

[7] Specifically, properties were included if their financing included one or more of these HUD programs: Section 207/223(f) and Section 223(a)(7), which provide mortgage insurance for purchase or refinancing of existing multifamily housing, and Section 542, under which HUD provides mortgage insurance in a risk-sharing agreement with state HFAs that lend to affordable housing projects. Section 8 contract renewal terms were measured in months from the date of renewal to the date of expiration. A small number of contracts had terms of 228 to 239 months; that is, 20 years minus a few months. These were included in the top category to account for delays in the contract renewal process that might slightly shorten the term.

[8] Note that the preservation analysis includes only properties with opt-ins during the 2005-to-2014 study period. It does not include previously preserved properties where the owner did not make an active opt-in choice between 2005 and 2014. For example, properties would not be included if they completed Mark-to-Market restructuring and signed a 20-year Section 8 contract prior to 2005.

Prevalence of Preservation Transactions

Use of the preservation tools was widespread among opt-in properties. In all, 3,561 properties with 328,394 units underwent at least one potential preservation transaction. This amounts to 28 percent of opt-in properties and 34 percent of units.

Exhibit 7 shows the distribution of opt-in properties across combinations of preservation interventions. It also shows the length of the term for the last Section 8 contract renewal executed during the 2005-to-2014 study period.

Among LIHTC-funded developments, most were funded using 4-percent credits, alone (830 properties/53 percent) or in combination with 9-percent credits (438 properties/28 percent). 9-percent credits alone were used only 19 percent of the time (285 properties).[9]

A common use of the HUD tool was the refinancing of direct loans from HUD's Section 202 program. From 1959 to 1990, the 202 program provided 40- to 50-year low-interest loans to nonprofit organizations for construction, rehabilitation, and acquisition costs for housing for elderly residents and persons with disabilities. HUD provides owners of Section 202 developments with the option to prepay and refinance 202 loans to reduce interest rate and debt service and to make capital improvements (HUD, 2013a). Nearly half (44 percent) of HUD-financed preservation properties in the opt-in dataset had inactive Section 202 loans. The preservation and stability of Section 202 developments are explored in more depth in Ray et al. (2015).

Exhibit 7

Opt-In Properties by Preservation Transactions and Contract Renewal Length

Preservation Indicator	Total Properties	Section 8 Renewal Term (%)		
		1–5 Years	5–18 Years	19 Years or More
LIHTC only	1,559	33	7	61
HUD refinancing only	1,045	NA	NA	100
Mark-to-Market only	240	15	27	59
LIHTC with HUD	279	NA	NA	100
LIHTC with Mark-to-Market	86	9	16	74
Mark-to-Market with HUD	282	NA	NA	100
All three programs	70	NA	NA	100
All preserved	3,561	16	5	79
All nonpreserved	9,111	62	6	32

HUD = U.S. Department of Housing and Urban Development. LIHTC = Low-Income Housing Tax Credit Program. NA = not applicable.

Notes: Renewal term refers to last contract renewal executed during the 2005–2014 study period. HUD refinancing was used as a preservation indicator only if the property also had a contract renewal of at least 19–20 years, so all HUD-financed preserved properties are in the 19 Years or More category by definition. Also, Mark-to-Market properties are required to remain affordable for 30 years, so shorter-term contracts are expected to be renewed.

Sources: HUD, 2005 and 2014 active properties, active financing, and active contracts files, Integrated Real Estate Management System; National Housing Preservation Database

[9] Percentages refer to developments for which credit type was available in the NHPD (1,556 of 1,994 developments).

Length of Affordability

The preservation tools appear to be effective in ensuring long-term affordability. Most of the preserved properties were operating under rental assistance contracts with terms of 19 to 20 years or more by the end of the 2005-to-2014 period (exhibit 7). All HUD-refinanced preservation properties were operating under contracts of at least 20 years by our own preservation definition, but the long-term contracts were also prevalent among LIHTC-only preservation properties (68 percent), Mark-to-Market-only properties (59 percent), and LIHTC/Mark-to-Market properties (74 percent). Moreover, LIHTC-funded properties are further protected by tenant income and rent restrictions extending at least 30 years from the date of tax credit funding, and longer in some states. Three-fourths of LIHTC-preserved opt-in properties in the dataset had income and rent restrictions extending until 2030 or later, including 32 percent with restrictions extending beyond 2040.

Nonpreserved properties were far more likely to be operating under short-term contracts. Of nonpreserved properties, 62 percent were operating under contracts renewed for 5 years or less at the end of the 2005-to-2014 study period. Although many owners do continue to renew short-term Section 8 contracts when they expire, the short-term contracts leave the opt-out choice open at every renewal point. These properties will require special attention and expansion of preservation initiatives to ensure that they continue to remain affordable.

Preservation Status and Opt-Out Risk Factors

Although preservation transactions offered widespread and long-term affordability protections, the record of targeting these protections toward properties most at risk of opt-out was mixed. Exhibit 8 shows the prevalence of the key opt-out risk factors among properties with each type of preservation transaction, compared with the nonpreserved opt-in properties.

Preservation efforts using LIHTC and Mark-to-Market do appear to be more targeted toward properties with two key opt-out risk factors: for-profit/limited dividend ownership and family occupancy. First, most properties with LIHTC funding and, in particular, Mark-to-Mark restructuring were owned by for-profit or limited dividend corporations. In contrast, most nonpreserved properties were owned by nonprofits. Note that this risk factor tracks the ownership type at the 2005 baseline; some of the preserved properties may have been transferred to nonprofit organizations subsequently as part of the preservation transaction. Second, most LIHTC and Mark-to-Market properties were designated for family occupancy, compared to a minority of nonpreserved properties.

In contrast, preserved developments with HUD-insured mortgages were less likely than nonpreserved properties to be owned by for-profits or to have family occupancy. This is linked to the heavy use of HUD refinancing to preserve properties with Section 202 loans. The 202 program requires elderly or disabled occupancy type and nonprofit ownership.

The other risk factors generally were equally or even less prevalent among the preserved properties compared to other opt-ins. Two risk factors stand out. First, small properties are at heightened risk of opt-out, but preservation resources were disproportionately found in larger properties. Half of the nonpreserved properties had fewer than 50 units, but only about one-fourth of the preserved properties did. Second, rent-FMR ratios below 80 percent were not more prevalent among

Exhibit 8

Presence of Risk Factors Among Opt-In Properties by Preservation Type

Risk Factor	Properties in Preservation Category With Risk Factor (%)							
	LIHTC Only	HUD Refinancing Only	Mark-to-Market Only	LIHTC With HUD	LIHTC With Mark-to-Market	Mark-to-Market With HUD	All Three Programs	All Non-preserved
Rent-to-FMR ratio < 80% (percent of properties)	11	3	5	6	8	2	4	11
For-profit/limited dividend ownership (percent of properties)	62	24	87	56	93	88	91	36
Family occupancy (percent of properties)	54	15	68	39	70	63	66	38
1–49 units (percent of properties)	29	28	24	19	19	29	21	51
Share of 0- to 2-bedroom units (average for properties)	85	96	81	88	79	80	80	90
Partially assisted (percent of properties)	16	7	6	13	14	5	11	14
Neighborhood poverty rate (average for properties; lower is risk factor)	23	20	30	22	25	26	27	21
Neighborhood homeownership rate (average for properties; lower is risk factor)	49	53	46	49	51	50	52	53
Neighborhood rent/county rent ratio (average for properties; higher is risk factor)	89	92	86	90	87	91	84	92

FMR = Fair Market Rent. HUD = U.S. Department of Urban Housing and Development. LIHTC = Low-Income Housing Tax Credit Program.

Sources: U.S. Department of Housing and Urban Development, 2005 and 2014 active properties, active financing, active contracts, and multifamily building type files, Integrated Real Estate Management System; terminated contracts database; terminated multifamily mortgages database; U.S. Census Bureau, 2005–2009 American Community Survey; National Housing Preservation Database

LIHTC-preserved properties than nonpreserved properties, and they were nearly absent among the HUD-financed and Mark-to-Market properties.[10] That is, it does not appear that LIHTC and other preservation resources were particularly targeted toward properties whose low rents compared to the surrounding market may encourage owners to convert to market rate.

Similarly, preservation resources do not appear to have been targeted toward neighborhoods with demographic and market conditions that raise opt-out risk. Averages for neighborhood indicators such as poverty rate, homeownership rate, and the ratio of neighborhood to county median rents were similar between preserved and nonpreserved properties. In fact, compared to the nonpreserved properties, Mark-to-Market properties were in neighborhoods with higher poverty rates and lower neighborhood rent-county rent ratios—both factors that point away from opt-out risk.

To summarize, a substantial number of opt-in properties have received preservation assistance. The preservation interventions are working as intended by encouraging long affordability periods, in contrast to the short contract renewal periods common among unpreserved properties. Preservation interventions have been effectively targeted toward properties with two well-understood risk factors, for-profit ownership and family occupancy. Other identified risk factors such as small property size, low rent-FMR ratios, and strong neighborhood market characteristics are not more prevalent among preserved properties. Future preservation initiatives can further reduce the risk of opt-outs by more careful targeting of developments with these characteristics.

Conclusion

The comparison of property outcomes between Finkel et al. (2006) and this update shows how HUD's multifamily portfolio has shifted in the last two decades. The Section 8-assisted inventory demonstrated more continuity between 2005 and 2014 than in the original 1998-to-2004 study period, even as HUD's original 221(d)(3) and 236 subsidized mortgage programs were largely phasing out. Fewer properties underwent opt-out, and far fewer were subject to foreclosure and contract abatement. At the same time, more owners actively opted to continue participation in the Section 8 program.

The 2005-to-2014 analysis shows that to the extent Section 8 opt-outs continued to occur, many properties were subject to similar risk factors to those identified in the original study, including family occupancy, for-profit ownership, low rent-FMR ratios, and location in less distressed neighborhoods. Although these factors were present in the second study phase, several were less influential. The descriptive cross-tabulations showed more variability in these characteristics among the properties lost to the affordable inventory, and the regression analysis showed that together these characteristics explained less variation in the opt-in/opt-out decision than before. For example, of the 748 opt-outs, over one-third (271, or 36 percent) was owned by nonprofit organizations, served elderly or disabled tenants, or both.

[10] The lack of Mark-to-Market properties with rents below 80 percent of FMR is to be expected. Mark-to-Market is targeted toward properties with *above*-market rents. For properties that had not completed the Mark-to-Market process at the time of contract renewal during the 2005-to-2014 study period, the rent-FMR ratio would reflect the above-market rents. For those that had completed restructuring, it still is unlikely that rents would be reduced as far as a level below 80 percent of FMR.

The analysis shows that a significant minority of the remaining Section 8 properties operate under conditions that protect them from opt-out risk. Thousands of properties operate under extended affordability periods associated with preservation financing tools. In particular, preservation with LIHTC has extended affordability periods for many Section 8 developments well into the future. Most of the preserved properties are owned by for-profit corporations and serving families, two characteristics that signaled higher opt-out risk in both the original study and the 2005-to-2014 update.

At the same time, the preservation analysis points up risk to properties without these additional interventions. The majority of Section 8 contracts in nonpreserved developments were renewed for terms of 5 years or less. The preservation tools do not seem to be targeted toward small developments in strong neighborhood and regional housing markets—exactly the types of properties that might be at risk of market-rate conversion as rental markets tighten and neighborhoods revitalize or gentrify. Preserving these developments may require efforts that bundle several small properties into single transactions or new financing tools that can be scaled for small developments.

We suggest several additional areas of research to improve our understanding of risks and preservation in the assisted housing inventory. First, we recommend detailed, year-over-year analysis of contract renewal histories to determine the extent to which the proliferation of short-term renewals signals future risk to the inventory. Do owners who renew a contract for 1 to 5 years tend to renew these contracts again upon expiration, or do short-term renewals signal an impending opt-out? Constructing full opt-in histories will require annual Section 8 contract datasets. The two point-in-time datasets available for this study provided a partial picture of renewals, but information was not available about short-term renewals in the intervening years between 2005 and 2014.

Second, given the weakened influence of the traditional opt-out risk factors, we recommend further examination of opt-outs in developments without these risk factors. These include developments serving elderly residents or persons with disabilities, nonprofit-owned properties, and developments that do not appear to be especially vulnerable to market-rate conversion (for example, those in distressed neighborhoods or whose contract rents are in line with or higher than the surrounding market rate). Case studies could help us understand the factors that lead to non-traditional opt-outs, such as changes in nonprofits' interest and ability to maintain aging subsidized properties.

Third, we recommend more indepth analysis of state policies on the use of LIHTC to preserve the HUD-assisted inventory. As noted previously, nearly all states provide some type of set-aside or other incentive to promote use of tax credits for preservation. These policies are present in states' Qualified Allocation Plans (QAPs) and other public documentation of scoring for LIHTC competitive allocations. Do states with robust preservation incentives in their QAPs report more opt-ins, potential preservation actions, and 20-year Section 8 contract renewals compared to states with weaker incentives? What types of incentives are most effective in promoting preservation?

Finally, the changes between Finkel et al. (2006) and this update demonstrate the value of continuing to update property characteristics and opt-in/opt-out histories. Conditions in the assisted housing inventory are not static. Ownership changes. Properties may age and deteriorate, or they may be rehabilitated. Length of remaining affordability changes over time; even 20-year contracts put into place in the early part of the 2005-to-2014 study period are already more than halfway to their expiration date. Neighborhood and regional housing markets also are not static. With rental markets tightening and affordable housing in short supply, properties in neighborhoods where opt-outs would have seemed unlikely in the past may become ripe for market-rate conversion. Accurate and up-to-date property information will be critical to continue the preservation efforts that have successfully maintained the assisted housing inventory.

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Authors

Anne Ray is Manager of the Florida Housing Data Clearinghouse at the University of Florida, Shimberg Center for Housing Studies.

Jeongseob Kim is an assistant professor at Ulsan National Institute of Science and Technology.

Diep Nguyen is a database manager at the University of Florida, Shimberg Center for Housing Studies.

Jongwon Choi is a doctoral student in the Department of Urban and Regional Planning at the University of Florida.

Kelly McElwain is a research analyst III at the Public and Affordable Housing Research Corporation and is the database manager of the National Housing Preservation Database.

Keely Jones Stater is Director of Research and Industry Intelligence at the Public and Affordable Housing Research Corporation.

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The Quality of Assisted Housing in the United States

Sandra Newman
Scott Holupka
Johns Hopkins University

Abstract

This article uses the 2011 American Housing Survey to develop three indices of housing quality, test their validity, apply them to both the assisted and unassisted stock, and assess whether the Fair Market Rent (FMR) aligns with good assisted housing quality. The market value index, developed using hedonic regression, performs poorly and is dropped from further consideration. The consumer rating index, based on an ordered logistic regression of the respondent house rating on a 1-to-10 scale, and the normative standards index, based on a factor analysis, perform well, are highly correlated, and achieve convergent and predictive validity. Both of these indices indicate that the quality of assisted housing is comparable to that of unassisted housing. The analysis also supports the 40th percentile of rents definition of the FMR, which is roughly the inflection point for maximizing assisted housing quality on both housing quality indices tested. The findings demonstrate that the current inspection and quality control systems appear to be achieving the goal of providing physically adequate housing to assisted housing residents.

Introduction

The U.S. Department of Housing and Urban Development (HUD) plays a key role in designing, implementing, and monitoring most of the nation's assisted housing programs, including public housing, privately owned, publicly subsidized housing (commonly referred to as "multifamily"), and vouchers.[1] Central to this responsibility is ensuring that the units receiving HUD assistance are physically adequate. This, in turn, verifies that recipient households live in decent and safe dwellings and reassures the public that tax dollars are not supporting deficient housing, or worse.

[1] This article is based heavily on Newman and Holupka (2017), which contains greater detail along with additional analyses, tables, and appendices.

To accomplish this objective, HUD imposes a set of housing quality standards (HQS) that assisted units must meet, requires periodic inspections to confirm that standards are being met, and when necessary, issues citations of violations that must be corrected within a specified time frame.[2]

Several recent circumstances prompt a reexamination of assisted HQS. First, HUD's *Strategic Plan 2014–2018* calls for the development of a "uniform asset risk assessment management model," which requires systematic evidence on the most meaningful approaches to measuring the quality of the assisted housing stock (HUD, 2014: 19). Second, the fiscal year 2013 Senate Appropriation Committee Report raises concerns about violations of HQS in housing units participating in the Section 8 voucher program and "directs HUD to take meaningful and timely steps to strengthen oversight and quality control" of the public housing agency (PHA) inspection process (U.S. Senate, 2012: 92). An additional concern is that reports by HUD's Office of the Inspector General and the U.S. Government Accountability Office note poor reliability of assisted housing inspections using the HQS (HUD OIG, 2008; GAO, 2000). This conclusion is based on a comparison of the PHA inspector scores with those collected by an independently trained rater.

This article is designed to contribute to the reexamination of assisted housing quality. We develop composite measures or indices of housing quality, test their validity, and apply them to both assisted and unassisted housing to examine possible disparities in quality between these two housing stocks. We also examine how well assisted housing quality aligns with HUD's Fair Market Rent (FMR). A longstanding policy question is whether good housing quality in the assisted stock aligns with the FMR, now generally set at the 40th percentile of rents in each housing market. One objective in setting the FMR at a particular point in the distribution of rents is the household's ability to find physically decent rental housing at or below the FMR threshold.

The analysis relies on rich data from the 2011 American Housing Survey (AHS) to describe the quality of the assisted housing stock and to highlight geographic areas, types of households, housing types, and housing assistance programs most likely to experience quality problems. The 2011 AHS sample was matched to administrative records on assisted housing receipt, alleviating concerns about the validity of self-reported housing assistance receipt.

It is important to acknowledge at the outset that the concept of housing quality is not based on definitive criteria and has no precise quantifiable definition of where "bad" ends and "good" begins (Newman, 2008). As we subsequently explain more fully, because we lack a consensus definition of housing quality, we construct measures that characterize the dwelling's physical integrity (for example, holes in the floor) or housing systems (for example, heating system breakdown) and exclude those that are more likely to reflect the resident's housekeeping or behavior (for example, leaving unsafe chemicals within a child's reach).

We find that the quality of assisted housing is comparable to the quality of unassisted housing. Multivariate models reveal modest heterogeneity in assisted housing quality, with the Northeast region and households that include a disabled member experiencing lower housing quality than

[2] Inspection protocols and processes differ by program. Public housing and multifamily housing—for example, Section 8 new construction; Section 221(d)(3)—must meet property standards, while Section 8 vouchers must meet HQS. Inspectors employed by the local public housing agency conduct inspections on public housing and voucher housing, while inspectors contracted by the HUD regional offices inspect multifamily housing.

average. The analysis also provides hard evidence supporting HUD's definition of the FMR as the 40th percentile of rents. The FMR is set at a level that is roughly at the inflection point for maximizing assisted housing quality as measured by the housing quality indices developed in this article.

The next section reviews the literature on housing quality, emphasizing past research on *assisted* housing quality. This is followed by a discussion of the research approach, including a description of the AHS data, analysis samples, methods, alternative measures of housing quality, and tests of their validity. We then examine assisted housing quality compared with unassisted housing quality, whether assisted housing quality varies by where it is located, such as in a central city or a suburb, or the characteristics of the residents. We also explore how well assisted housing quality aligns with the FMR. The final section discusses the results and their implications for policy and future research.

Literature Review

The substantial literature on housing quality spans nine decades and demonstrates both the importance and the challenges of conceptualizing and measuring housing quality. Three relevant strands characterize past work: housing quality measurement and data collection methods, the AHS measurement of housing quality, and the quality of assisted housing.

Housing Quality Measurement and Data Collection Methods

The American Public Health Association provided some of the earliest contributions to the housing quality literature. APHA (1938) highlighted the connection between housing conditions and health, and APHA (1945) recommended that data be collected through a field survey of many individual features of each dwelling unit, with penalty scores for each feature that falls below an established standard. The sum of all scores represents the quality of the dwelling. This methodology is roughly similar to that used for physical inspections of assisted housing under HUD's Uniform Physical Condition Standards (UPCS).[3]

Another important early contribution was the U.S. Census Bureau's methodological study of housing quality measurement (Census Bureau, 1967).[4] For decades, the decennial census included interviewer observations of housing features. In 1940, housing condition was measured by a dwelling's "state of repair," with trained enumerators rating the structure as either needing "major" repairs or not. In 1950, this approach was replaced by another dichotomous classification of structures as either "dilapidated" or "not dilapidated." This dichotomy was refined in 1960 by further classifying those structures designated as "not dilapidated" as either "sound" or "deteriorating." Following the 1960 census, the Census Bureau launched a detailed and thorough evaluation of its approach to measuring housing conditions that resulted in the 1967 publication. Its unambiguous conclusion was that

[3] UPCS currently exists for public housing and for multifamily housing. A version for the voucher program, UPCS-V, is under development and will replace the current HQS system (Cota, 2017).

[4] This discussion draws on Newman (2008).

housing conditions collected through interviewer observations are unreliable and, therefore, inaccurate. As a result, subsequent decennial censuses that relied on interviewers to administer the survey dropped the interviewer observations of housing unit condition. The AHS followed suit in 1997.[5]

Alongside concerns in the literature about the best way to collect data on housing quality is the issue of the best way to measure housing quality. Curiously, much more attention has been paid to developing a summary measure than to identifying the individual housing features that should comprise the summary measure. The pioneering work of Kain and Quigley (1970) established the feasibility of using housing unit measures of quality as predictors of house prices and rents, also known as hedonic models. The coefficients in these models can be viewed as weights in a hedonic price index. Kain and Quigley's work led to a burgeoning of hedonic modeling over the ensuing decades (for example, Coulson and Li, 2013; Kriström, 2008; Merrill, 1980; Thibodeau, 1995). Three features of Kain and Quigley's approach are particularly relevant to the current article. First, they apply factor analysis to reduce the 39 separate measures of housing quality in their St. Louis survey data to a manageable number. Second, they find that the seven survey measures pertaining to the quality of the individual dwelling unit interior formed a single index or factor.[6] Third, in multivariate hedonic regressions, the dwelling unit quality factor has a statistically significant effect on rent. Consistent with most of the literature in this area, the authors do not take on the question of how best to conceptualize housing quality and, instead, assume that this concept is captured by their 39 variables pertaining to "the physical or visual quality of the bundle of residential services" (Kain and Quigley, 1970: 534).

AHS Measurement of Housing Quality

The AHS is the most comprehensive data source on the U.S. housing stock.[7] Policymakers, practitioners, and researchers seeking answers to questions about the conditions, costs, and various other attributes of the nation's housing rely on it. It is also relied on as a source of housing questions for those developing their own surveys. A prominent example is the Moving to Opportunity for Fair Housing Demonstration (Shroder, 2001). Of particular interest to many users is the AHS composite measure of housing inadequacy available on the public use database, which is a variable labeled ZADEQ. The measure combines multiple items on housing conditions into an index, setting numerical thresholds for the presence or absence of physical deficiencies in the dwelling to distinguish among "adequate," "moderately inadequate," and "severely inadequate" units. Both the AHS and data users refer to this composite as the "AHS housing quality measure." Numerous published articles include the AHS measure in their analyses (for example, Carter, 2011; Friedman and Rosenbaum, 2004; Khadduri, 2007; Ross, Shlay, and Picon, 2012). It plays a prominent role in HUD's *Worst Case Housing Needs* reports (for example, HUD, 2015) and is also included in the frequently cited Joint Center for Housing Studies' *The State of the Nation's Housing* reports (for example, JCHS, 2017) and Millennial Housing Commission (2002). However, not until the last few years was the AHS quality measure subjected to careful examination.

[5] The AHS began interviewing returning households by phone, when possible, in 1997. In 2011, a phone-first policy was instituted for both new and returning households (Vandenbroucke, 2016).

[6] Their survey included many other items focusing on the condition of adjacent structures, parcels, and block faces, along with the structure's exterior condition.

[7] Drawn in part from Newman and Garboden (2013).

Eggers and Moumen's (2013a) analysis of the 2005, 2007, and 2009 AHS data implicitly raises some concerns about whether the ZADEQ measure accurately reflects the quality of the housing stock. The measure produces a very low prevalence of severe inadequacy (2 percent); only two items—sharing a bathroom and heating problems—account for most of the cases considered severely inadequate, and these problems generally do not persist over a 2-year period. The authors also conclude that the shared bathroom item is likely to have been measured incorrectly. More generally, they conclude that the AHS quality measure may provide a reasonable cross-sectional estimate of the most severely inadequate units, but provides little information on the roughly 91 percent of units considered adequate.[8]

In a second paper, Eggers and Moumen (2013b) proposed an alternative to ZADEQ that is designed to provide more information about gradations within the adequate housing stock. A major motivation is their particular interest in being able to study filtering, which requires a measure that reveals increases in deficiencies or inadequacies over time as a unit deteriorates and is presumably filtered down from higher income to lower income residents. They develop an alternative measure, the poor quality index (PQI), which is a numeric scale of housing defects that draws on additional measures in the AHS (for example, exterior structure) along with those included in ZADEQ. Lacking a reliable source on how to weight each item in the index, they assign weights based on a combination of ZADEQ's definitions and their own judgment. The PQI appears to achieve the goals of its creators. By contrast to ZADEQ, which estimates that a large majority of units had no problems, 47 percent of units had at least one PQI inadequacy.[9] The stability of the classification of the unit also differs for the two indices (Eggers and Moumen, 2013b). With ZADEQ, 95 percent of adequate units in one survey remain adequate 2 years later, whereas roughly 30 to 35 percent of units categorized as moderately or severely inadequate in one survey remained inadequate in the subsequent survey. Using the PQI, a smaller share, 63 percent of units, remained adequate from one survey to the next, and a greater share of inadequate units, roughly 60 percent, retained that designation over 2 years.

Emrath and Taylor (2012) examined the AHS ZADEQ index using a hedonic model. Because of the multicollinearity among the individual measures that comprise ZADEQ, the authors test each ZADEQ item separately, along with other features of the dwelling (for example, number of rooms, geographic region, and square footage). They report that none of the ZADEQ items reach statistical significance and, in some cases, have an unexpected sign. A major policy concern of the authors is that the very small rate of housing units meeting the definition of physically inadequate using ZADEQ leads to the conclusion that the nation's housing stock has no serious housing problems. They challenge this conclusion by identifying measures in the AHS, many of which are not included in ZADEQ, that have a strong effect on rents and prices. These items are similar to those included in Eggers and Moumen's (2013b) PQI. It is likely that Emrath and Taylor's ZADEQ results occur because of the very low variance of each individual item. This was part of Kain and Quigley's (1970) motivation for using factor analysis, which produced a single dwelling unit quality factor.[10]

[8] Authors' estimate based on the 2011 AHS.

[9] The PQI rate is based on the 1993 AHS. Because the two Eggers and Moumen reports (2013a; 2013b) rely on different AHS years, it is impossible to make direct comparisons between ZADEQ and PQI results.

[10] Merrill (1980) applied a somewhat similar approach in her hedonic modeling using data from the Experimental Housing Allowance Program demand experiment.

A fourth recent paper assesses the reliability, consistency, and validity of the AHS ZADEQ index (Newman and Garboden, 2013). Like Eggers and Moumen (2013a; 2013b) and Emrath and Taylor (2012), the authors conclude that the index identifies only a very small share of units with multiple inadequacies and provides little information about variations among units classified as adequate. They also find that the items included in the index do not appear to be tapping the same underlying construct of housing quality. However, the two subindices within ZADEQ, moderate inadequacy and severe inadequacy, are strong and statistically significant predictors of residents' housing satisfaction.

Quality of Assisted Housing

The research literature on the physical quality of the assisted housing stock is sparse, at least in part, because the AHS, the main data source on housing, typically relies on respondent self-reports of the receipt of housing assistance, which are known to be unreliable (Shroder, 2002). The present article utilizes the 2011 AHS data, which identifies assisted housing receipt, by program type, on the basis of a match to administrative records, not self-reports. Validation of assisted housing receipt was previously done in the 1989 AHS.[11] One paper used these validated data and a version of ZADEQ to study the assisted housing profiles of households with children (Newman and Schnare, 1993). The authors report that 15 percent of public housing units occupied by households with children had either a moderate or severe defect, compared with 5 percent of multifamily housing and 12 percent of voucher units. The average number of defects, however, was generally similar across the programs.

A more recent study examined the quality of housing in the voucher program (Buron et al., 2003). Data on voucher housing come from the 2000 Customer Satisfaction Survey (CSA). The authors developed two measures of housing quality, one relying on all quality-related items in the CSA and another using CSA items that align with those in the AHS. The CSA-based measure was used to explore voucher-housing quality, and the CSA-AHS measure was used to compare housing quality in the voucher program with housing quality in a matched comparison sample of unassisted renters. The CSA-based summary measure combined items into four categories: (1) severely inadequate quality, (2) moderately inadequate quality, (3) adequate quality, and (4) high quality. Based on voucher respondent reports to the CSA, 41 percent of voucher housing was considered high quality, 33 percent adequate quality, 4 percent moderately inadequate, and 23 percent severely inadequate (numbers rounded). The rate of severe inadequacy is higher than the 12- to 21-percent range in Gray, Haley, and Mast (2008), HUD's report on the first-year results of the CSA, which relied on similar though not identical quality measures. Buron et al. (2003) based their analysis of voucher and comparable nonvoucher housing quality on a statistical match between the households in the CSA voucher sample and households in the AHS. They use two different measures of housing quality, one a simple count of problems aggregated into four categories (0, 1–2, 3–4, and 5+ problems) and another indicating whether at least one problem was reported for each of five housing dimensions (for example, kitchen and bathrooms; electrical). Both measures yield the similar finding of lower-quality housing of voucher users than housing occupied by unassisted

[11] Documentation on this validation can be found in Newman and Schnare (1993).

renters. For example, 59 percent of voucher renters reported no housing problems compared with 66 percent of unassisted renters. The authors cautioned that differences between the CSA and AHS may account for some or most of these disparities.

Research Approach

In the next section, we describe the AHS data we use in the analysis, the analysis samples and the different facets of our methodological approach. We also review the three main alternative measures of housing quality that are the focus of our analysis.

Data

The main data source for the current analysis is the 2011 AHS. The AHS began in 1973 and is sponsored by HUD and conducted by the Census Bureau. As previously noted, the 2011 assisted housing cases are identified based on matching sample addresses to HUD administrative data on HUD-assisted housing programs.[12] The sample includes 9,721 assisted housing units[13] and 40,030 unassisted rental housing units in single-family or multifamily properties, the housing types that dominate the assisted stock.[14] Because we will ultimately apply the quality indices to the assisted stock, we rely on the unassisted sample to develop the housing quality indices. These indices are based on 33 housing quality items that are collected from both single-family and multifamily rental units.

Methods

Construction of the Comparison Groups

We compare the quality of assisted housing to two comparison groups of unassisted housing, one including all rentals and the other limited to units with rents at or below the FMR. For both comparison groups, we limit cases to units in a single-family or multifamily property and exclude unassisted cases that are rare or nonexistent in the assisted stock (for example, manufactured housing; reduced rents because of relationship between renter and landlord). We also exclude vacant or vacation units and units where no interview was conducted.[15]

Housing Quality Indices

Because the concept of housing quality is not based on explicit criteria, the large number of housing quality indices that have been developed with the AHS yield dramatically different prevalence rates (Newman and Schnare, 1988). The core challenge is well known; a housing unit is a bundle of attributes that extend beyond the dwelling itself, and it is unclear which of these attributes

[12] The match to HUD data excludes housing units assisted by state and local programs and the federal Low-Income Housing Tax Credit (LIHTC) program, which is under the auspices of the Department of the Treasury. However, because a sizable share of LIHTC units also receives HUD subsidies, such as vouchers, these units are included in the HUD administrative files. O'Regan and Horn (2012) estimated that 46 percent of LIHTC households receive some form of rental assistance, Buron et al. (2000) put the estimate at 37 percent, and GAO's (1997) estimate is 39 percent.

[13] Based on sample design appendix to 2011 AHS documentation (HUD, 2011).

[14] See Newman and Holupka (2017), table A1 for all selection criteria for the unassisted sample.

[15] Supplementary analysis using propensity score matching to create comparison groups produce similar results.

should be included in the definition of the dwelling's quality and how each should be weighted in determining overall quality (Aaron, 1972; Merrill, 1980). In the absence of a consensus view, the next best option is to rely on an external criterion, as suggested by Merrill (1980). We examine three alternatives: market value, consumer rating, and normative standards.

Market Value Index. The market value approach assumes that the unit's rent is correlated with the quantity and quality of housing such that higher rents reflect better quality. Consistent with the literature (for example, Coulson and Li, 2013; Kriström, 2008; Thibodeau, 1995), this theory can be tested with a hedonic regression where the dependent variable is the natural log of rent and covariates include characteristics of the housing bundle. In this article, covariates include multiple features of the housing unit, geographic location, the respondent's rating of the neighborhood (the only neighborhood measure available in the 2011 AHS), and the FMR. Although our main interest is the contribution of housing quality to market value, this effect could depend on the nonhousing features included in the model, such as perceived neighborhood quality or location in a central city or suburb. Because of substantial multicollinearity among the 33 housing quality items, we estimate two hedonic models, one including all 33 items despite this collinearity problem, and the other testing each of the 33 items separately.

Consumer Rating Index. The consumer rating criterion identifies the dwelling features that are most closely associated with the resident's assessment of the dwelling as a good place to live, regardless of what the market price of these features might be. This criterion broadens the concept of housing quality beyond specific housing features to the welfare of residents as they themselves report it (Goodman, 1978). It is consistent with the renewed interest by economists in happiness and subjective well-being as a measure of the utility an individual derives from goods and services (Dolan, Peasgood, and White, 2008).

The AHS question asks the respondent: "On a scale of 1 to 10, how would you rate your unit as a place to live?" Although the original coding designates 10 as best and 1 as worst, we reverse these codes for consistency with the normative standards index (discussed next). Thus, a higher value on this ordinal scale indicates lower housing quality. We test the consumer rating model using ordered logistic regression, which generates coefficients expressed as odds ratios: how much a unit change in housing quality item X changes the house rating. As with the market value criterion, we test the consumer rating index using each individual quality item separately and all quality items combined. Because the results are similar, we only present the results from the separate quality measure tests.

Normative Standards Index. The normative standards criterion is designed to reflect community concerns and policy decisions about housing quality, such as state building codes and assisted housing physical inspection standards. We use factor analysis to develop the normative standards index. Factor analysis examines the correlations among measures to determine the amount of common variance among them. The analysis produces factor "loadings," which indicate how much variance is shared among the observed measures and the unobserved construct (here, housing quality). The loadings or scores constitute the weights that we use to create the factor analysis index. Because many of the quality measures are dichotomous, we estimate polychoric correlations

(Jöreskog and Sörbom, 1996). Following Preacher et al. (2013), we select the smallest number of factors for which the root mean square error of approximation (RMSEA) is below 0.05. This approach identifies the measures that most accurately reflect housing quality.

Assessing Index Validity. We assess the convergent and predictive validity of the resulting housing quality indices (Carmines and Zeller, 1979). Convergent validity is based on the correlations among the indices and between each index and other attributes with which the index should be associated, such as the resident's house rating or satisfaction. Predictive validity is based on the predictive power and significance of the indices in multivariate models predicting two outcomes, the resident's house rating on a 0-to-10 scale and rent.

Assisted Housing Quality

The analysis of assisted housing quality proceeds in three steps. First, we begin by examining differences between the assisted and unassisted housing stock for each of the 33 individual housing quality measures included in the housing quality indices. This analysis also includes three additional measures from the 2011 AHS Healthy Homes modules. Second, we look at variations in quality within the assisted housing stock by program type, household type, and location. Because most of these analyses are based on the large sample sizes available in the AHS, measures of statistical significance are not very useful to gauge substantive importance. Therefore, we rely heavily on the size of the effect as measured by Cohen's *d*.[16] In a final step, we estimate a series of multivariate models predicting each housing quality index controlling for housing, location, and household characteristics. The first set of models is limited to the assisted housing sample, and includes assisted housing program type as one of the explanatory variables. The second set of models includes both assisted and unassisted housing, initially testing assisted housing as a whole, and then distinguishing this stock by program type. Because the data are heavily skewed, and the distributions have considerable dispersion, we use negative binomial modeling as the estimation technique.

Assisted Housing Quality and FMRs

To explore the alignment between the FMR and assisted housing quality, we calculate each household's housing cost relative to the FMR (that is, gross rent divided by the FMR). We then divide this relative housing cost scale into equal units (for example, 40 to 45 percent of the FMR, 45 to 50 percent of the FMR, and so on) so that the FMR, the 40th percentile, sits in the middle of the distribution.

Results

Exhibit 1 lists the AHS housing quality measures in this analysis and their means. Consistent with much past AHS housing quality research, the prevalence rates of almost all problems are very low. Most (55 percent) dwellings have no problems, and fewer than 5 percent of units account for more than 75 percent of problems.

[16] Cohen's *d* is the difference in means between two groups divided by the standard deviation for the pooled sample of the two groups (Cohen, 1977).

Exhibit 1

2011 AHS Housing Quality Measures, Mean Prevalence Rates for U.S. Rental Housing

	Mean Prevalence Rate	Average for Counts
Not all rooms have plugs	1	
# times blown fuses last 3 months	9	0.23
Exposed wiring	2	
Unit does not have electricity	0.03	
Unvented room heaters	1	
No heating equipment	1	
Use stove/oven for heat	0.1	
# heating breakdowns last winter	3	0.8
Unit cold 24+ hours last winter	10	
Cold due to utility interruption last winter	1	
Cold due to inadequate heating capacity last winter	2	
Cold due to inadequate insulation last winter	2	
Cold due to other reason last winter	2	
Roof leak last 12 months	5	
Leak in wall/closet last 12 months	3	
Leak in basement last 12 months	1	
Leak other source last 12 months	1	
Leaking pipes last 12 months	5	
Leaking plumbing fixture last 12 months	2	
Leak unknown source last 12 months	4	
Crack in wall	7	
Holes in floor	1	
Peeling paint	3	
Signs of rodents last 12 months	3	
Signs of rats last 12 months	1	
Signs of mice last 12 months	9	
Signs of cockroaches last 12 months	5	
Incomplete plumbing	0.3	
# times toilet broke 6+ hours last 3 months	2	0.05
Share plumbing facility	2	
Incomplete kitchen	4	
# sewage disposal breakdowns last 3 months	1	0.03
No working elevator	5	
Any mold	5	
Broken/missing steps	1	
Broken/missing stair railings	1	

AHS = American Housing Survey.

Notes: N = 40,830 unassisted rental units from 2011 AHS. Excludes manufactured housing and units where a relationship exists between renter and landlord. See Newman and Holupka (2017) text and Appendix Table A-1 for more details. Weighted data. Average times for counts = average for entire sample, including zeros for those not reporting the problem. "# times no water last 3 months" never reported and we do not include in the exhibit. Last three items from Healthy Homes module.

Housing Quality Indices

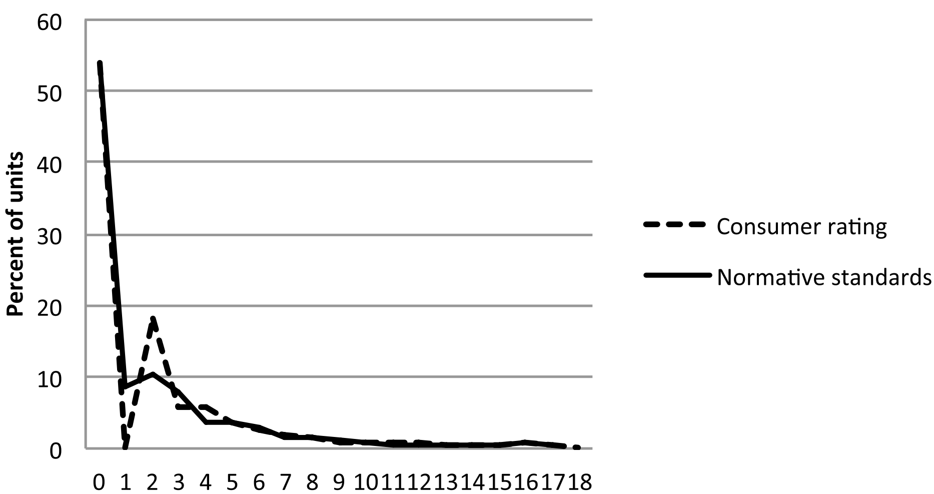
Despite its intuitive appeal and the rich hedonic literature, the market value index performs poorly. Roughly 85 percent of the AHS housing quality items either do not reach statistical significance despite the very large sample, or operate in the opposite direction of expectations. The results do not appreciably improve after adjusting the threshold required for statistical significance using the Bonferroni correction to account for multiple comparisons. The results also are remarkably consistent whether each item is tested separately or they are combined. It is likely that the rarity of each individual quality problem provides too little variance to make a meaningful contribution to the rent. In addition, rent appears to have a nonlinear relationship with the quality index. Rents are essentially flat across most of the distribution of the housing quality index but then fall significantly at the tail that represents the most housing problems. However, the hedonic formulation assumes a linear relationship between rent and dwelling features. Given its poor performance, we drop the market value housing quality index from the rest of the analysis.[17]

In contrast to the market value index, both the consumer rating index and the normative standards index perform well. The scores on both of these indices are highly skewed, as vividly demonstrated in exhibit 2. Most housing units have none of the 33 housing quality problems included in this analysis, with only a small fraction experiencing one or more problems.

As shown in exhibit 3, the consumer rating index model has strong explanatory power and the large majority of items operate in the expected direction (that is, odds ratio greater than 1).[18] Most of the items are also statistically significant although, as previously noted, this is a less useful test given the large sample size. The five measures that make the largest contribution to house rating are (1) holes in the floor, (2) peeling paint, (3) cracks in the walls, (4) presence of rodents, and (5) cold due to inadequate insulation. For example, the presence of holes in the floor makes it 3.5 times more likely that the consumer's house rating is poorer, peeling paint makes a poorer score 3.3 times more likely, and rodents make this 2.7 times more likely. To create a housing quality index based on the consumer rating criterion, we use the odds ratio for each quality measure as a weight.

Exhibit 2

Distribution of Consumer Rating and Normative Standards Index Scores



Note: High values for both indices converted into categories: 16 = 15 to 20; 17 = 20 to 30; and 18 = 30+.

[17] See Newman and Holupka (2017), table 3.

[18] One exception is the use of an oven for heat, which affects a very small proportion of rental units (see exhibit 1).

Exhibit 3

Housing Quality Predictions of Consumer Rating Index

	Odds Ratio	*p*-Value	
Not all rooms have plugs	1.973	.000	***
# times blown fuses last 3 months	1.175	.000	***
Exposed wiring	1.363	.000	***
Unit does not have electricity	1.770	.573	
Unvented room heaters	1.075	.588	
No heating equipment	1.261	.106	
Use stove/oven for heat	0.725	.269	
# heating breakdowns last winter	1.225	.000	***
Unit cold 24+ hours last winter	2.017	.000	***
Cold due to utility interruption last winter	1.731	.000	***
Cold due to inadequate heating capacity last winter	2.212	.000	***
Cold due to inadequate insulation last winter	2.656	.000	***
Cold due to other reason last winter	1.531	.000	***
Roof leak last 12 months	1.987	.000	***
Leak in wall/closet last 12 months	1.801	.000	***
Leak in basement last 12 months	1.921	.000	***
Leak other source last 12 months	1.541	.000	***
Leaking pipes last 12 months	1.678	.000	***
Leaking plumbing fixture last 12 months	1.904	.000	***
Leak unknown source last 12 months	1.482	.000	***
Crack in wall	2.708	.000	***
Holes in floor	3.509	.000	***
Peeling paint	3.253	.000	***
Signs of rodents last 12 months	2.657	.000	***
Signs of rats last 12 months	2.127	.000	***
Signs of mice last 12 months	1.626	.000	***
Signs of cockroaches last 12 months	2.052	.000	***
Incomplete plumbing	1.430	.197	
# times toilet broke 6+ hours last 3 months	1.275	.000	***
Share plumbing facility	1.111	.172	
Incomplete kitchen	1.208	.000	***
# sewage disposal breakdowns last 3 months	1.243	.000	***
No working elevator	1.262	.002	**

*** $p < .001$. ** $p < .01$.

Notes: Results from 33 separate ordinal logistic regressions on subjective housing rating (reverse coded so high score = poorer quality). Other covariates in each regression include dummy variables for room air conditioner, central air conditioner, dishwasher, garbage disposal, clothes dryer, washing machine, electric heat, gas heat, oil heat, den/TV room, dining room, family room, working fireplace, garage/carport, half-bathrooms, laundry room, porch/deck/patio, connected to public sewer, use well water, electricity included in rent, gas included in rent, oil included in rent, and other fuel included in rent. Also included in the regressions are number of bathrooms; number of bedrooms; number of floors in unit; number of floors in building; building age; building age squared; building age cubed; unit type (for example, single-family, single-family attached, multifamily); number of months in unit; neighborhood self-rating; and U.S. Department of Housing and Urban Development Fair Market Rent. N = 36,833. Odds ratio = e^{β} where "β" is the coefficient from the logistic model.

In the normative standards index based on a factor analysis, the RMSEA results support the use of a one-dimensional index for measuring housing quality. These results also provide weights for an index based on the factor scores.[19] The factor loadings, shown in exhibit 4, are consistent with

[19] Both the average and lower bound of the RMSEA scores are below 0.05, the criterion set by Preacher et al. (2013) for selecting the number of factors. See Newman and Holupka (2017), table 6.

Exhibit 4

Housing Quality Components of the Normative Standards Index

	Factor Analysis Weights
Not all rooms have plugs	1.000
# times blown fuses last 3 months	0.921
Exposed wiring	1.465
Unit does not have electricity	1.649
Unvented room heaters	0.968
No heating equipment	– 1.435
Use stove/oven for heat	– 1.497
# heating breakdowns last winter	0.747
Unit cold 24+ hours last winter	3.340
Cold due to utility interruption last winter	2.593
Cold due to inadequate heating capacity last winter	2.626
Cold due to inadequate insulation last winter	—
Cold due to other reason last winter	2.184
Roof leak last 12 months	2.019
Leak in wall/closet last 12 months	1.920
Leak in basement last 12 months	1.755
Leak other source last 12 months	1.454
Leaking pipes last 12 months	1.812
Leaking plumbing fixture last 12 months	1.787
Leak unknown source last 12 months	1.263
Crack in wall	2.667
Holes in floor	2.702
Peeling paint	2.685
Signs of rodents last 12 months	3.629
Signs of rats last 12 months	2.441
Signs of mice last 12 months	2.783
Signs of cockroaches last 12 months	2.071
Incomplete plumbing	1.629
# times toilet broke 6+ hours last 3 months	0.717
Share plumbing facility	0.270
Incomplete kitchen	0.707
# sewage disposal breakdowns last 3 months	0.207
No working elevator	0.482

Notes: Factor analysis estimated in Mplus using polychoric correlations. "Cold due to inadequate insulation last winter" dropped from factor analysis because perfectly it correlated with other measures.

the odds ratios produced by the consumer rating model. The highest factor loadings are presence of rodents; number of times the dwelling was cold for 24 hours or longer; presence of mice; holes in the floor; peeling paint; and cracks in the walls. Items with the lowest factor loadings include using the oven for heat; lacking heating equipment; number of toilet breakdowns lasting 6 hours or longer; incomplete plumbing; and sharing plumbing facilities.[20]

[20] The reference variable is whether all rooms have electrical outlets ("plugs" in exhibit 1).

Validity Tests

The consumer rating and normative standards indices are highly correlated (r =.967, p =.000 with two-tailed test), suggesting that they appear to be measuring the same underlying phenomenon and, therefore, have strong convergent validity. It is worth noting that two additional indices we developed that are more ad hoc versions of a normative standards index also are highly correlated with both the consumer rating and normative standards factor analysis indices. One ad hoc index applies the weights from Eggers and Moumen (2013b), which are based on a combination of the AHS ZADEQ housing quality measure and the authors' judgment, whereas the other simply assigns a weight of 1 to each of the 33 housing quality items (see Newman and Holupka, 2017, table 8).

Exhibit 5 shows the results for a second test of convergent validity—the correlations between each housing quality index and other AHS measures associated with housing quality. In addition to actual and logged rent, house rating, and building age, we also include the AHS' ZADEQ.[21] All of the correlations are statistically significant and operate in the expected direction. Although the correlation between each index and ZADEQ is higher than it is with rent, house rating, and building age, it is less than half the correlation between the consumer rating and normative standards indices.

The predictive validity of the two housing quality indices is somewhat mixed. As shown in exhibit 6, both the consumer rating index and the normative standards factor analysis index are significant predictors of the respondent's rating of their house on a 10-point scale. Poorer housing quality, indicated by higher scores on each index, is associated with a worse (that is, higher) house rating even after controlling for household and geographic location characteristics. The coefficients suggest that a one standard deviation increase in each index produces nearly a 20-percent improvement (that is, reduction) in house rating. However, the consumer rating index is not a statistically significant predictor of rent (although it has the expected negative sign), and the normative standards index is statistically significant only at the more liberal .10 level. The unusual shape of the relationship between rent and each index—essentially flat until the highest values at the tail of the index—may contribute to the muted statistical significance.

Exhibit 5

Convergent Validity: Correlations With AHS Measures Related to Housing Quality

	Consumer Rating Index	Normative Standards Index
Rent	– .017***	– .022***
	(.000)	(.000)
Log rent	– .015***	– .019***
	(.000)	(.000)
House rating	– .341***	– .338***
	(.000)	(.000)
Building age	.214***	.223***
	(.000)	(.000)
ZADEQ	.419***	.375***
	(.000)	(.000)

AHS = American Housing Survey.
*** p < .001.
Notes: Weighted data. Two-tailed significance test. ZADEQ is a measure of housing unit quality computed in the AHS.

[21] The respondent's housing rating is distinct from the consumer rating index. The house rating measure is the respondent's rating, from 1 to 10, of the dwelling as a good place to live, without any direct reference to the 33 quality measures. By contrast, the index assigns weights to each of the 33 quality measures based on the respondent's dwelling rating.

Exhibit 6

Predictive Validity of Housing Quality Indices: Regression Results for Rent and House Rating

	Consumer Rating Index	Normative Standards Index
Log rent	– 1.518	– 2.376+
	(.157)	(.055)
House rating	.848***	.830***
	(.000)	(.000)

+ $p < .10$. *** $p < .001$.

Notes: Top number is regression coefficient for rent, odds ratio for house rating. Bottom number is p*-value. Log rent uses ordinary least squares, house rating uses ordinal logistic regression. Log rent models also control for log household income; household head's age, race, and ethnicity; air conditioning; washer and dryer; type of heat; fireplace; garage; laundry room; porch; number of rooms; pay for utilities; number of months in unit; age of building; area Fair Market Rent; number of bedrooms; number of bathrooms; and geographic location (region and central city, suburban, or rural). House rating models also control for log household income; household head's age, gender, race, and ethnicity; and geographic location (region and central city, suburban, or rural).*

Assisted Housing Quality

Exhibit 7 compares the quality of the assisted and unassisted stock. As shown in the column headings, we define two unassisted housing comparison groups: housing units with rents that equal or fall below the FMR, and all rental units. Results from a more rigorous approach to matching assisted and unassisted cases through propensity score matching (PM) produced similar results to those shown in the table.[22] The table includes 36 housing quality items—the 33 we have referred to throughout this article plus three additional items from the AHS Healthy Homes module: mold, broken railings, and broken steps.

Although the difference in housing quality between the assisted and unassisted stock is statistically significant in more than half of the 36 quality items, statistical significance is not a sensitive test with very large samples. A more useful metric is the effect size, measured by Cohen's *d*. As the table shows, none of the housing quality items that achieve statistical significance at the $p \leq .001$ (for example, problems with heating, roof leaks, or rodents) attains a Cohen's *d* of 0.2, the accepted threshold for a small effect. Thus, it is not surprising that the consumer rating and the normative standards index scores also do not differ for the two housing stocks. This leads to the conclusion that, based on the housing quality items examined here, the quality of assisted housing is comparable to the quality of unassisted housing. This conclusion applies whether we limit the unassisted stock to units with rents at or below the FMR, to all unassisted rental units, or to propensity score-matched assisted and unassisted units.

Within the assisted housing stock, although the consumer rating and normative standards housing quality index values are always worst for public housing and best for multifamily housing, the effect sizes never reaches the 0.2 threshold for a small effect (not shown). Characterizing assisted housing by a three-category household type measure—elderly, nonelderly family, nonelderly disabled—reveals that assisted housing for the elderly enjoys the best housing quality and housing for

[22] PM models controlled for an array of both household and housing unit characteristics. Results available from the authors.

Exhibit 7

Prevalence Rates of 2011 Housing Problems, by Housing Assistance Receipt

	Assisted Housing Versus Rentals ≤ FMR				Assisted Housing Versus All Rentals		
	Assisted Housing	Unassisted Housing		Cohen's *d*	Assisted Housing	Unassisted Housing	
Not all rooms have plugs	1.3	1.1	+		1.3	0.9	**
Ever blown fuses	8.6	8.9			8.6	9.3	+
# times blown fuses	22.1	22.3			22.1	23.3	
Exposed wiring	2.8	2.3	*		2.8	2.2	**
Unit does not have electricity	0.00	0.02			0.00	0.03	
Unvented room heaters	0.3	1.3	***	.091	0.3	1.0	***
No heating equipment	0.2	1.0	***	.094	0.2	0.7	***
Use stove or oven for heat	0.1	0.2			0.1	0.1	
Ever heating breakdowns	4.6	3.4	***	.060	4.6	3.1	***
# times heating broke down	11.3	9.4	+		11.3	8.1	***
Unit cold 24+ hours last winter	17.5	12.3	***	.100	17.5	11.3	***
Cold: utility interruption	1.2	1.1			1.2	1.0	
Cold: inadequate heating	3.0	2.2	**		3.0	1.9	***
Cold: inadequate insulation	2.3	1.8	*		2.3	1.7	***
Cold: other reason	2.3	1.8	*		2.3	1.5	***
Roof leak last 12 months	3.2	5.3	***	.098	3.2	4.9	***
Leak in wall/closet	3.4	3.0	+		3.4	2.9	*
Leak in basement	1.3	1.2			1.3	1.4	
Leak other source	1.4	1.3			1.4	1.3	
Leaking pipes	5.4	5.2			5.4	4.9	
Leaking plumbing fixture	2.4	2.4			2.4	2.4	
Leak unknown source	5.0	3.7	***	.069	3.6	5.0	***
Cracks in walls	7.5	7.7			7.5	6.9	
Holes in floor	2.1	1.6	*		2.1	1.4	***
Peeling paint	3.9	3.7			3.9	3.1	***
Signs of rodents	5.3	4.0	***	.066	5.3	3.1	***
Signs of rats last	1.1	1.3			1.1	1.2	
Signs of mice last	12.8	10.2	***	.087	12.8	9.0	***
Signs of cockroaches	5.8	6.3			5.8	4.5	***
Incomplete plumbing	0.2	0.5	**		0.2	0.3	
Toilet ever broke	3.3	2.5	***	.048	3.3	2.3	***
# times toilet broke	6.7	4.9	**		6.7	5.0	**
Share plumbing facility	2.3	1.7	**		2.3	1.6	***
Incomplete kitchen	4.8	4.3			4.8	4.0	**
Ever sewage breakdown	1.5	1.5			1.5	1.3	
# sewage breakdowns	3.8	3.2			3.8	3.0	
No working elevator	6.1	4.7	***	.066	6.1	5.0	***
Any mold	8.0	8.5			8.0	7.9	
Broken/missing steps	0.6	0.8			0.6	0.8	
Broken/missing stair railings	0.9	1.2			0.9	1.3	+

FMR = Fair Market Rent.

*+ p < .10. * p < .05. ** p < .01. *** p < .001.*

Notes: Assisted housing N = 8,472; All rentals unassisted housing N = 40,830; Rentals ≤ FMR unassisted housing N = 24,190. Weighted data. Average for counts ("#") = average for entire sample, not just those reporting the problem. Cohen's d computed for all effects significant at .001 or less. Values < 0.2 indicate virtually no difference.

the nonelderly disabled has the worst.[23] As shown in exhibit 8, the difference in the index scores of these two household types reaches a medium effect size (0.50 for consumer rating and 0.51 for normative standards). Bivariate analysis of additional housing, household, and location attributes suggests other variations in housing quality within the assisted stock. These include whether the unit is located in a central city, suburb or rural area, household size, and region. A central city location is associated with a worse score on both housing quality indices (Cohen's d = 0.24 to 0.25), as the household size grows, quality worsens (Cohen's d = 0.65 to 0.68), and assisted housing in the Northeast has the worst quality ratings (Cohen's d = 0.41 to 0.45).

Multivariate models predicting the housing quality score on each of the two indices, controlling for housing, location, and household characteristics, produce very similar results to those in the bivariate descriptive analysis. We estimate two sets of regression models using negative binomial modeling to account for the severe skew in the housing quality indices.[24] The first is limited to the assisted housing sample and the policy variable of primary interest is assisted housing program type (the voucher program is the excluded category). Next, we pool the assisted and unassisted housing samples and test whether, all else equal, living in assisted housing has a sizable effect on the housing quality index score, and then test whether the assisted housing program type affects the housing quality index score.

Exhibit 9 displays the results. Regardless of whether the sample is limited to the assisted housing stock (the top set of rows) or includes both the assisted and unassisted stock (the bottom set of rows), none of the odds ratios on any of the assisted housing measures, whether the general category or distinguished by program type, achieves even a small effect size despite several statistically significant coefficients (Chen, Cohen, and Chen, 2010). Among the other covariates, only two—whether anyone in the household is disabled and whether the household lives in the Northeast region—have small effect sizes in each of these models. Holding other characteristics constant, households living in the Northeast and those with a disabled member have worse housing quality.

Exhibit 8

Housing Quality Index Ratings of 2011 Assisted Housing Units, by Household Type

	Consumer Rating Index	Normative Standards Index
Elderly	1.71	1.57
< 62 disabled	3.79	3.45
< 62 family	2.57	2.31
p-value	.000	.000
Cohen's *d*	.500	.514

Notes: Weighted data. Elderly n = 3,165; < 62 disabled n = 1,597; < 62 family n = 2,648. Excludes 14 percent of assisted housing cases where head < 62, not disabled, and no children. p*-value tests significance of difference among all three groups. Cohen's* d *compares "elderly" to "< 62 disabled." Values < 0.2 indicate virtually no difference.*

[23] The AHS does not identify housing for the elderly, families, or young disabled. To construct these categories, we assume a household head 62 years of age or older is living in elderly housing, that families with children 18 or younger and without a disabled member are living in family housing, and that nonelderly persons younger than 62, even if they are living with family members, are in housing for the disabled. This is admittedly a very blunt approach but is the best that can be done with the AHS data.

[24] More than one-half of the samples report no housing quality problems in either index, the dispersion ratios are roughly 1.8, and the standard deviation is nearly twice as large as the mean.

Exhibit 9

Multivariate Models Predicting Housing Quality Index Ratings

	Negative Binomial	
	Odds Ratio	*p*-Value
Assisted housing only		
Consumer rating index		
Public housing	.952	
Multifamily	.987	
Normative rating index		
Public housing	.924	
Multifamily	.962	
Assisted and unassisted (≤ FMR) housing		
Consumer rating index		
Assisted housing	.925	*
Normative rating index		
Assisted housing	.956	
Consumer rating index		
Public housing	.869	*
Multifamily	.942	
Voucher	.934	+
Normative rating index		
Public housing	.894	*
Multifamily	.966	
Voucher	.970	

FMR = Fair Market Rent.

+ $p < .10$. * $p < .05$.

Notes: Total unweighted n = 25,808. Weighted data. Covariates: census region; metropolitan location; head's age, race, gender, and marital status; number of persons in household; whether anyone in household disabled; income quartile; and structure type. Because negative binomial models cannot use decimals, dependent variables multiplied by 100 and rounded. A small effect, equivalent to a Cohen's d of 0.2, would be an odds ratio > 1.4 if > 1 or < .71. Odds ratios between .71 and 1.4 are not significant. Vouchers excluded from assisted housing models; unassisted housing excluded from models pooling assisted and unassisted housing.

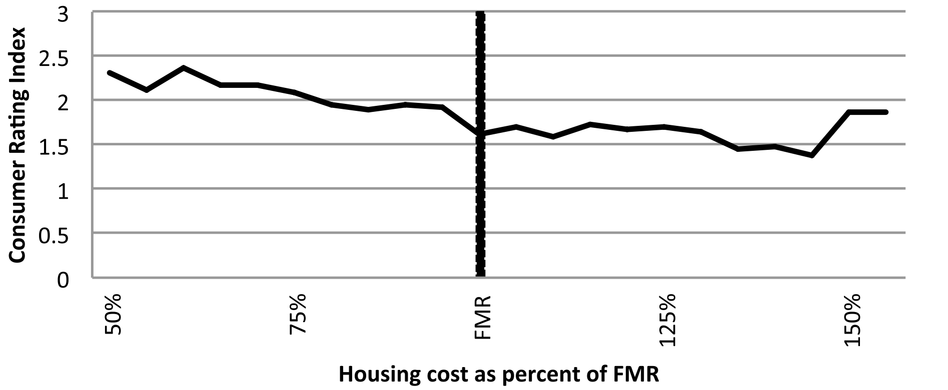
Assisted Housing Quality and Fair Market Rents

As noted in the discussion of methods, we develop a relative housing cost scale, gross rent divided by the FMR, to examine the relationship between the consumer rating housing quality index and the FMR. The results, graphed in exhibit 10, indicate that housing quality is maximized roughly at the FMR, indicated by the vertical line. The worst housing quality occurs at about the 24th percentile of rent.[25] In some cases, HUD approves payment standards up to 120 percent of the FMR, such as when a disabled household member requires reasonable accommodations in the voucher program. The figure shows no appreciable difference in housing quality between the FMR and 120 percent of the FMR. The results are similar for the normative standards index.

[25] This occurs at approximately the 60th percentile; that is, 60th x 40th (the FMR) = 24th.

Exhibit 10

Consumer Rating Index, by Relative Cost and FMR



FMR = Fair Market Rent.

*Notes: Housing cost = rent + utilities obtained from the U.S. Department of Housing and Urban Development Housing Affordability Data System. Housing cost relative to FMR = (Housing Cost / FMR) * 100. The consumer rating index top-coded at the 99th percentile to avoid outliers. FMR scale excludes top and bottom 5 percent to avoid outliers.*

Discussion

The substantial literature on housing quality demonstrates both the importance and the challenges of conceptualizing and measuring housing quality. The growing interest in how housing matters, primarily in the low-rent unassisted housing stock, and the ongoing concerns about HQS in the assisted stock, make this an opportune time to revisit housing quality. In this article, we review the relevant literature, develop alternative housing quality indices, test their validity, and apply them to both the assisted and unassisted housing stock. We focus on indicators of physical integrity of housing systems and exclude measures that are more likely to reflect residents' housekeeping or behaviors.

Because no consensus exists about the features of the housing bundle that should be included in the definition of a dwelling's quality and how each should be weighted in determining overall quality, we rely on three external criteria first suggested by research on the Experimental Housing Allowance Program (EHAP; Merrill, 1980): market value, consumer rating, and normative standards. We test the market value criterion with a hedonic approach. The consumer rating criterion identifies the dwelling features most associated with a resident's assessment of the dwelling as a good place to live regardless of what the market price of these features might be. This criterion is consistent with the renewed interest by economists in happiness and subjective well-being. The normative standards criterion reflects community concerns and policy decisions such as building codes. We rely on the 2011 national AHS for the analysis, which provides large national samples of the assisted and unassisted stock, and identifies assisted housing based on address matching to HUD administrative data, not respondent self-report.

Despite its intuitive appeal, the market value criterion performs poorly. This could occur because of the rarity of each item, or the nonlinearity of the relationship between rents and the housing quality index, which cannot be accommodated by the hedonic approach. However, it may also occur because the national sample comprises widely varying housing markets, and our controls for market attributes are relatively coarse. Another explanation is that the individual dwelling quality measures may not be the main drivers of rents, as suggested by Merrill (1980). Therefore, we drop this market value criterion from further analysis. These poor results call into question the applicability of hedonic models using individual measures of physical inadequacies as predictors for rental properties (for example, Emrath and Taylor, 2012). Merrill (1980) raised this same issue in her EHAP analysis.

For the consumer rating index, we use the odds ratios from ordered logistic regressions as the weights. For the normative standards index, we use weights derived from a factor analysis. Both of these indices perform well. Consistent with much past AHS housing quality research, the prevalence rate of almost all problems is very low, with most dwelling units having no problems. However, notable overlap occurs between the measures that are the strongest predictors of the consumer ratings index and the factor analysis normative standards index. These are presence of rodents, cold dwelling unit, holes in the floor, peeling paint, and cracks in the walls. These represent a mix of high and low prevalence dwelling conditions, which make this overlap of items between the two indices unlikely to be driven by simple math. The indices also achieve both convergent validity and predictive validity.

We find that the quality of assisted housing is comparable to the quality of unassisted housing. This conclusion applies whether we limit the unassisted stock to units with rents at or below the FMR, to all unassisted rental units, or to housing units emerging from statistically matching the assisted and unassisted units using PM techniques.

The type of assisted housing program does not appear to have an appreciable effect on housing quality. Although we control for an array of housing, household, and location characteristics in multivariate models predicting the housing quality score on either index, only two of these covariates—whether anyone in the household is disabled and whether the household lives in the Northeast region—achieves even a small effect, in both cases reducing housing quality.

This research provides hard evidence supporting the current 40th percentile of rents definition of the FMR. We find that the FMR is set at a level that is roughly at the inflection point for maximizing assisted housing quality as measured by the consumer rating and normative standards housing quality indices.

Overall, these positive findings demonstrating the comparable quality of the assisted and unassisted housing stock suggest that the current assisted housing inspection and quality control systems appear to be achieving the goal of providing physically adequate housing to assisted housing residents. They also lend support to the shift to biennial inspections in the voucher program and the biennial and triennial inspections for standard and high performers, respectively, in the public housing program. The findings reported may also be useful to HUD as it finalizes plans for a demonstration program to test a new approach to physical inspections including a single inspection protocol for public housing and voucher units.[26]

[26] See the joint Explanatory Statement accompanying the Consolidated Appropriations Act, 2016 (Pub. L. 114–113).

We view this research as one step along the path toward improving our understanding of housing quality. One important enhancement of this work would be to expand the measures to include additional aspects of the full housing bundle, particularly neighborhood features. Linking the AHS data via confidential geocodes to census tract data and an array of administrative data at the neighborhood level could accomplish that goal. Another extension would be to compare these results with housing inspection scores from HUD's administrative data (that is, the Public Housing Assessment System and Real Estate Assessment Center housing inspection ratings for public housing and multifamily housing, respectively). At the more conceptual end of the continuum, this article does not focus on what measures *should be* included in a measure of housing quality, only on how well the measures included in the AHS appear to be reliable and valid and form a coherent index. A consideration of what measures currently missing from the AHS should be included in the future is worth serious attention.

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Authors

Sandra Newman is a professor of policy studies at the Johns Hopkins University.

Scott Holupka is a senior research associate at the Johns Hopkins University.

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An International Perspective: Reflection on the Symposium

Kwan Ok Lee
National University of Singapore

For decades, housing affordability has remained one of the main issues in social science research in most developed countries. Therefore, I believe that the four articles in this *Cityscape* symposium will provide great insight to both domestic and international readers by documenting the recent state of housing assistance programs in the United States. I also appreciate the authors' efforts to tackle critical dimensions of U.S. federal housing programs, ranging from housing quality and preservation of assisted housing units to the mobility and cost burdens of tenants. As the findings of articles are quite relevant to the non-U.S. contexts, it is worth discussing how they can provide broader implications and some cross-country lessons, including how each article relates to other articles on similar topics in the international literature.

Ray et al. (2018) address the continuing loss of the assisted housing inventory, raising the question of the long-term sustainability of affordable housing. Both McClure (2018) and Dawkins and Jeon (2018) find temporal variation in the length of stay in assisted housing and housing cost burdens in the Housing Choice Voucher program—two critical issues in the stability of assisted housing programs. Some scholarly works in Asian countries share similar questions and tend to put an emphasis on the appropriate role of the government. In the case of Hong Kong, the government has effectively preserved the public rental housing stock through large-scale redevelopment of obsolete units even after its adoption of the Private Sector Priority Strategy, which actively involves the private sector in providing assisted owner-occupied units (La Grange, 1998). In Singapore, evidence suggests that the price movement of public and private housing markets are closely interrelated, and policies that aim at any change in supply, financing, or regulations affecting one market have significantly influenced the other market (Ong and Sing, 2002; Phang and Wong, 1997). Finally, Newman and Holupka (2018) focus on the quality of assisted housing and find that the government inspection and quality control systems play a role in providing physically adequate housing to assisted housing residents.

Although challenging in terms of collecting data and standardized measures, comprehensive, comparative analyses between different countries and among different assisted housing programs would be extremely useful for the future research. For example, unlike the United States, many countries including Singapore, China, and Hong Kong have successfully implemented place-based public housing programs. These countries have shown much stronger government commitment in public housing programs and adopted policy measures for ethnic integration and effective property management. Hence, it would be interesting to comparatively analyze key features of these programs and draw lessons from their successes and failures. A further discussion on the transferability of such successful programs would be informative to many scholars and policymakers who have to deal with broader housing affordability issues.

Author

Kwan Ok Lee is an assistant professor at the National University of Singapore.

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Prioritizing Homeless Assistance Using Predictive Algorithms: An Evidence-Based Approach

Halil Toros
Daniel Flaming
Economic Roundtable

Abstract

In this article, we present a predictive model for identifying homeless persons likely to have high future costs for public services. We developed the model by linking administrative records from 2007 through 2012 for 7 Santa Clara County, California agencies and identifying 38 demographic, clinical, and service utilization variables with the greatest predictive value. We modeled records for 57,259 individuals from 2007 to 2009, and the algorithm was validated using 2010 and 2011 records to predict high-cost status in 2012. A business case scenario shows that two-thirds of the top 1,000 high-cost users predicted by the model are true positives, with estimated posthousing cost reductions of more than $19,000 per person in 2011. The model performed very well in giving low scores to homeless persons with one-time cost spikes, achieving the desired result of excluding cases with single-year rather than ongoing high costs.

Overview

Homelessness is a major social problem in the United States, with large public health impacts affecting millions of individuals and families and costing billions of dollars. The most recent annual numbers available from the U.S. Department of Housing and Urban Development (HUD) are for 2016 and show 1,421,196 people used an emergency shelter or a transitional housing program at some point during the year (HUD, 2016). The most recent point-in-time numbers are for 2017 and show, on a night in January, 553,742 people were homeless. Among individuals, 24 percent were chronically homeless (HUD, 2017).

The health, personal, and economic challenges that chronically homeless individuals experience and the lack of effective, coordinated services to address these problems often lead to a vicious cycle of diminished well-being with serious implications for their service utilization patterns

(Economic Roundtable, 2015a). The impairments of some of these individuals might impede access to needed health services and other support systems, such as employment services. Consequently, they cycle through costly emergency-driven public systems without getting the ongoing care they need to address severe mental illness, substance use disorders, or chronic health conditions (Caton, Wilkins, and Anderson, 2007; Folsom et al., 2005).

The number of individuals experiencing homelessness substantially exceeds the number of affordable housing units available for them. This shortfall includes permanently affordable housing with supportive services that is needed for many chronically homeless individuals. Managing the gap between housing supply and demand is a challenge for city and county housing agencies. The predictive algorithm we describe provides a fair, objective tool for triage—prioritizing which individuals may receive Housing First.

Growth in homelessness over the last three decades has been exacerbated by economic downturns, loss of affordable housing and foreclosures, stagnating wages, an inadequate safety net, and the closing of state psychiatric institutions. In response to this growing need, the federal response to homelessness shifted in 2009 from uncoordinated short-term responses to avert homelessness—primarily using shelters—to long-term housing solutions. Permanent housing subsidies have since been shown to significantly increase housing stability, food security, and child well-being (Gubits et al., 2016).

The first component of the federal strategy shift was providing permanent supportive housing (PSH), that is, housing that is permanently affordable combined with ongoing supportive services for people experiencing chronic homelessness, and prioritizing those individuals with the most severe disabilities for assistance. The second component was connecting PSH to street outreach, shelter, and institutional "in-reach" to identify and engage people experiencing chronic homelessness. The third component was communitywide adoption of Housing First to provide permanent housing as quickly as possible in order to end chronic homelessness and prevent its recurrence (USICH, 2015).

The Housing First model was introduced by Pathways to Housing, a New York City nonprofit, to provide homeless intervention services to adults with psychiatric diagnoses and substance abuse problems. The nonprofit provided immediate housing and services to homeless adults with co-occurring diagnosis as a matter of right, with no preconditions. It also incorporated a harm reduction approach to psychiatric and substance abuse treatment and empowered the consumers of services to make choices about housing and services (Greenwood, Stefancic, and Tsemberis, 2013).

The Housing First approach makes housing stabilization the centerpiece of homeless assistance and recognizes that some people need more than housing assistance to stabilize. A small but highly visible segment of the chronically homeless population has substantial service needs. PSH with a Housing First approach enables chronically homeless individuals with disabilities that interfere with maintaining housing on their own to become stable renters.

PSH with a Housing First approach is an effective intervention for enabling chronically homeless individuals to permanently exit homelessness. However, because housing resources are limited, one of the key challenges is identifying and targeting the "highest priority" individuals so as to allocate scarce housing in a way that produces the greatest benefit. It is well documented that costly interventions, such as PSH, are not likely to generate cost offsets equal or higher than the cost of the interventions, except for the most costly users (Culhane, 2008; Poulin et al., 2010).

A 2015 study in Santa Clara County, California, confirmed that chronic homelessness is very costly. The 10 percent with the highest costs, the 10th decile, accounted for 61 percent of all public costs for homelessness, and the top 5 percent accounted for 47 percent of all costs (Economic Roundtable, 2015b). Studies in Los Angeles County found that PSH provided to chronically homeless individuals in the 10th decile generated large enough cost offsets to cover the costs of housing and services (Economic Roundtable, 2015b, 2009). However, the scarce supply of PSH is often rented out to the eligible population based on crude screening processes that rely on self-reported data. Given that PSH is proven to have a large impact on reducing chronic homelessness and associated public costs, a strong argument can be made for using more accurate screening tools to identify individuals who should have first priority for access to permanently affordable housing.

This article extends previous research applying predictive models to homelessness and high-cost service users. The model presented in this article predicts who will or will not become a high-cost public service user in the next year, given various person-level characteristics in the current year and previous year, providing a predictive score (probability) for each individual in order to determine housing priorities across large numbers of individuals.

Prioritizing high-cost homeless persons for whom the solution of housing costs less than the problem of homelessness improves the efficiency of PSH. Cost offsets from reduced service use after high-cost people are stably housed can be stretched across a larger pool of homeless people whose housing can be subsidized with those offsets.

This is a triage tool for connecting homeless persons who are high-cost users of public services with permanently affordable housing, community-based healthcare, and support services. The tool applies a statistical predictive model to administrative data in order to prioritize homeless adults with the highest needs and public costs. It provides highly accurate predictions comparable to those developed through studies of high-cost health system users. Because no other models predict high-cost service users within the homeless population, health sector models provide the closest comparison. These models identify patients at high risk of readmission to a hospital based on demographics, prior hospital admissions, and clinical conditions (Ash et al., 2001; Billings et al., 2013, 2006; Chechulin et al., 2014; Fleishman and Cohen, 2010; Moturu, Johnson, and Liu, 2010; Tamang et al., 2016).

This tool improves on earlier predictive models for identifying homeless individuals in the 10th cost decile (Economic Roundtable, 2012, 2011). Several other studies have also used predictive models to assess homeless risks. Byrne et al. (2016) estimated predictors of homelessness and developed methods for more efficiently targeting homeless prevention services. A recent study of the Home Base prevention program for families in New York City[1] showed that adoption of

[1] Home Base was a homeless prevention program operated by the New York City Department of Homeless Services from 2004 to 2008. Workers interviewed applicants about potential risk factors for homelessness, including human capital, housing conditions, disability, interpersonal discord, childhood experiences, and shelter history. The study compared the accuracy of judgments made by workers in determining eligibility for services to the results produced by a screening model in predicting whether families would enter a homeless shelter in the following 3 years.

an empirical model for deciding which families to serve can make homeless prevention more efficient (Shinn et al., 2013). Also, the U.S. Department of Veterans Affairs (VA) has explored using predictive models in screening homeless veterans (Montgomery et al., 2013). However, to date, no studies have examined the relationship of past service utilization to future high-cost homelessness using predictive algorithms to prioritize which homeless people get housing.

In this article, we describe the predictive modeling methodology used to develop a triage tool to prioritize housing access for an efficient and cost effective PSH program. After presenting the results and validation of the model, we develop a business scenario to estimate the cost savings after implementation of the triage tool. The article ends with a discussion of ways to use the tool, limitations of it, and recommendations.

Chronic Homelessness

The majority of people who become homeless remain so for less than a year. A smaller number of people, however, remain homeless much longer, experiencing continuous and chronic homelessness. According to federal guidelines, an individual is chronically homeless if he or she has a diagnosed disability—such as serious mental illness, substance use disorder, posttraumatic stress disorder, cognitive impairments or chronic physical illness or disability—and has been homeless and lives in a place not meant for human habitation, a safe haven, or in an emergency shelter for at least 1 continuous year or has experienced at least four episodes of homelessness in the past 3 years where the cumulative total of the four occasions is at least 1 year.[2]

Needs of chronically homeless individuals that are essential for their well-being go unmet, including connections to housing, income, family, and health. This leads to stress, anxiety, depression, deprivation, and chaos, thus destabilizing their lives. Over time, chronically homeless individuals have increasingly complex and costly needs, including serious health and mental health conditions and disabilities that result in cycling in and out of hospitals, jails, prisons, psychiatric hospitals, and homeless shelters.

Several studies describe the clinical and social characteristics and patterns of service utilization among people who are chronically homeless. The majority of individuals have a serious mental illness such as schizophrenia, bipolar disorder, or major depression. They also experience high rates of substance abuse disorders, physical disability, or chronic disease. Many experience co-occurring mental illness and substance use problems (Burt, 2002; Caton et al., 2005; Caton, Wilkins, and Anderson, 2007; Folsom et al., 2005; Rosenheck, 2000). In addition to serious disability, the lives of chronically homeless people are compromised by persistent unemployment and lack of earned income forcing dependence on public assistance for sustenance, healthcare, and, if fortunate, an eventual exit from homelessness (Caton et al., 2005; Caton, Wilkins, and Anderson, 2007). Moreover, chronically homeless individuals often have a long arrest history, cycling through jail and prison (Caton et al., 2005; Kushel et al., 2005; Metraux and Culhane, 2004; Zugazaga, 2004).

Chronically homeless individuals spend a disproportionate number of days in the shelter system (Kuhn and Culhane, 1998; Metraux et al., 2001). In addition, because of their complex and

[2] "Homeless Emergency Assistance and Rapid Transition to Housing: Defining 'Chronically Homeless.'" *Federal Register* 80 (75791–75806). 2015. https://www.hudexchange.info/resource/4847/hearth-defining-chronically-homeless-final-rule/.

co-occurring disabling conditions, poor health status, and elevated rates of unintentional injuries and traumatic injuries from assault, chronically homeless persons have high rates of hospital emergency rooms use and hospitalization, and longer hospital stays for mental health and substance abuse problems (Culhane, Metraux, and Hadley, 2002; Folsom et al., 2005; Kuno et al., 2000; Kushel et al., 2002). As the chronically homeless population ages, its utilization of emergency rooms and hospital rooms increases (Caton, Wilkins, and Anderson, 2007). High incarceration rates, coupled with heavy use of mental health and medical facilities in jails and prisons are also well documented (Kushel et al., 2005; McNiel, Binder, and Robinson, 2005; Metraux and Culhane, 2004).

Heavy use of acute and behavioral healthcare, criminal justice involvement, and use of social services may cost tens of thousands of dollars per individual annually (Ly and Latimer, 2015; Culhane, Metraux, and Hadley, 2002; Gilmer et al., 2009; Larimer et al., 2009; Martinez and Burt, 2006; McLaughlin, 2011). Although chronically homeless people represent only 20 percent of shelter users, they consume the largest share of health, social, and justice services with enormous costs (Ly and Latimer, 2015). In Los Angeles County, among homeless recipients of General Relief cash aid,[3] the highest cost decile accounted for 56 percent of all public costs for homeless single adults (Economic Roundtable, 2011, 2009). A recent study using Santa Clara County data also showed that public costs for homelessness are heavily skewed toward a comparatively small number of frequent users of public and medical services. Among residents experiencing homelessness in 2012, the 10th decile, accounted for almost two-thirds of costs, and the top 5 percent accounted for almost half of costs (Economic Roundtable, 2015b).

Federal funding for homeless programs increased from $3.7 billion in 2010 to nearly $5.5 billion in 2016 (USICH, 2016). In addition, federal expenditures for homeless individuals are also distributed through Medicaid, Medicare, and the VA, as well as large expenditures by state and county governments and institutions such as hospitals, jails, and social service agencies.

Although public outlays to address chronic homelessness have been growing since 2010, the prevalence and costs of homelessness remain high. With finite resources for homeless assistance, prevention services and cost-effective interventions, such as PSH, have attracted growing interest from policymakers and academic research over the past decade (Apicello, 2010; Burt and Pearson, 2005; Byrne et al., 2014; Culhane, Metraux and Byrne, 2011).

Preventive Services and Permanent Supportive Housing

The logic of prevention requires definition of what is to be prevented (such as chronic homelessness) and specification of the association (preferably causal) between the intervention and prevention of the undesirable condition. Several frameworks have been suggested for developing prevention strategies for homelessness (Burt and Pearson, 2005). The high-risk framework is the most appropriate framework for conceptualizing how to design homeless prevention policies because it draws attention to the need for direct intervention among those individuals at greatest risk. This framework focuses on alleviating the causes of homelessness for the most vulnerable subpopulations (Apicello, 2010).

[3] General Relief is a cash aid program that provides a maximum of $221 a month for destitute adults. Roughly two-thirds of the caseload is estimated to be homeless. This program is called General Assistance in other California counties.

To be successful, prevention strategies for high-risk individuals need to be both effective and efficient (Burt and Pearson, 2005; Culhane, Metraux, and Byrne, 2011; Shinn, Baumohl, and Hopper, 2001). In this context, effectiveness refers to how capable a program is of facilitating the desired goal—prevention of homelessness with reasonable costs. Effectiveness should be evaluated with robust designs by comparing a treatment group of persons who received services to a control group of individuals not subject to the intervention. Otherwise, the effect of the services in preventing homelessness cannot be assessed accurately, because it is unrealistic to assume that all the people who received services would have become or stayed homeless in the absence of those services. It is also possible that the effect of services might have not been significant; homelessness might have been merely postponed; or the ranks of high-risk individuals might simply have been reshuffled, allowing some to "jump the queue" and push others back in the line (Shinn, Baumohl, and Hopper, 2001).

As noted previously, recent research has shown that PSH, using a Housing First approach, is a very effective homeless prevention service and has led to widespread and successful efforts to reduce chronic homelessness (Byrne et al., 2014; Culhane, Metraux, and Hadley, 2002; Greenwood, Stefancic, and Tsemberis, 2013; Larimer et al., 2009; Rog et al., 2014; Tsemberis and Eisenberg, 2000; USICH, 2015, 2010). Based on increasing evidence, the U.S. federal government has endorsed PSH using a Housing First approach as the "clear solution" to chronic homelessness, and PSH has become an important priority for HUD. The number of beds in PSH projects increased nearly 60 percent between 2007 and 2014, when an estimated 285,400 people lived in PSH (HUD, 2014; USICH, 2010).

Research has also demonstrated the effectiveness of PSH in generating cost offsets. Many studies have shown that PSH and Housing First interventions for chronically homeless individuals lead to cost savings through reduced shelter costs, decreases in both psychiatric and medical inpatient hospitalization costs, lower emergency room visit costs, reduced substance abuse treatment costs, and reduced criminal justice costs due to fewer arrests, detentions, and court appearances (Culhane and Byrne, 2010; Henwood et al., 2015; Ly and Latimer, 2015; Martinez and Burt, 2006; Shinn, Baumohl, and Hopper, 2001; Shinn et al., 2013; Toros and Stevens, 2012). Cost savings from providing PSH to homeless people with mental disorders was shown to be substantial (Culhane, Metraux, and Hadley, 2002; Gilmer et al., 2009; Larimer et al., 2009; McLaughlin, 2011; Sadowski et al., 2009).

Despite such successes, the high cost of PSH would limit its availability to chronically homeless individuals with the greatest service needs if cost offsets are the benchmark for determining eligibility. Culhane (2008) reviewed several studies and concluded PSH is not likely to generate cost offsets equal to the cost of the interventions, except for the most costly users. Other studies also support the view that only frequent users of higher-cost services are likely to have sufficiently high costs to fully or mostly offset the costs of a PSH placement. Some research indicates that group may be limited to the most costly 10 percent of the chronically homeless (Poulin et al., 2010; Rosenheck, 2000). Moreover, since homeless people are typically placed in PSH programs at times when they are in crisis and have had relatively high service use, regression to the mean results in decreasing costs for many of these people, even if they are not placed in PSH (Ly and Latimer, 2015).

Hence, the research demonstrates that, although PSH is effective in reducing chronic homelessness and yields significant cost offsets, to be efficient, it should target high-cost homeless persons so that offsets will cover program and housing costs. In the context of homeless prevention, efficiency refers to targeting high-risk individuals. Efficient targeting is critical in the design and success of prevention services (Apicello, 2010; Burt and Pearson, 2005; Culhane, Metraux, and Byrne, 2011; Shinn, Baumohl, and Hopper, 2001). An efficient program should use empirically and/or theoretically derived risk factors to identify high-risk individuals who are likely to stay homeless and use costly public services unless they receive the prevention services.

However, the efficiency criterion introduces a serious challenge. Predictive models and screening tools are subject to the well-known tradeoff between sensitivity (the probability of correctly identifying true positives, or those individuals who will remain or become low-cost persons in Santa Clara County in the absence of the prevention program) and specificity (the probability of correctly identifying true negatives, or those individuals who would stay as low-cost homeless persons). If a low cutoff is selected, while the sensitivity increases and the model capturing more true positives, the specificity decreases leading to higher numbers of false positives. On the other hand, fewer false positives occur if the targeting cutoff is increased but many true positives are missed. This difficult tradeoff is at the core of the efficiency issue, as savings realized through placing a high-cost homeless person in PSH will be washed out if many low-cost homeless persons are also placed (Culhane, Metraux, and Byrne, 2011).

In the literature, it is argued that the common failing of many prevention efforts is their targeting inefficiency, which leads to ineffective programs (Burt and Pearson, 2005). It is also argued in the literature that available screening models are not sensitive or accurate enough to yield high hit rates without missing a large number of high-risk persons who would benefit from the program while producing cost savings (Apicello, 2010; Shinn, Baumohl, and Hopper, 2001). However, recent technological advances in the fields of predictive analytics and data mining together, with the availability of digital integrated administrative datasets with rich service utilization fields, allow significant improvement in prediction ability over earlier approaches and models (Larson, 2013).

This article presents the Silicon Valley Triage Tool. The County of Santa Clara supported the development of this tool so that it could identify homeless individuals in jails, hospitals, and clinics who have continuing crises in their lives that create very high public costs, and also give them first priority for access to PSH. This effort took roughly 2 years and included linking records of homeless clients across county agencies, analyzing attributes and costs for these individuals, and developing the triage tool. The model is very robust and accurate, taking advantage of advanced prediction methodologies and a unique and exceptionally valuable database created by Santa Clara County, home to Silicon Valley, linking service and cost records across county departments for the entire population of residents who experienced homelessness over a 6-year period—a total of 104,206 individuals. The tool accurately identifies individuals experiencing homelessness whose acute needs create the greatest public costs and is expected to serve as a screening tool for efficient and effective PSH programs.

Methods

Four steps were involved in developing the Silicon Valley Triage Tool: first, linking agency records to create an integrated dataset; second, analyzing the data and developing the triage tool; third, testing and validating the tool; and fourth, developing a business model to project cost savings from using the tool. Each step is described in the following sections.

Data

By collaborating in linking their client records, seven agencies in Santa Clara County[4] provided information on medical care (inpatient and outpatient), Emergency Medical Services (EMS), drug and alcohol treatment services, mental health treatment services (inpatient and outpatient), incarceration (arrest, court, and medical and mental health services in custody), and HUD-funded social and homeless services (Economic Roundtable, 2015b).

The Silicon Valley Triage Tool was developed using records for a subgroup of the total population that experienced homelessness. This subgroup included 57,259 individuals who used a homeless service and also had a linked record in another agency during the 6-year study window from 2007 through 2012. This subgroup of records was used to develop the triage tool so as to avoid using records that may have had incomplete data because of uncompleted linkages across some agencies.

We benchmarked the tool against the total population that was homeless during the 6-year time window rather than just against individuals who were documented as being homeless at a specific time. We considered this time period because the problems that result in chronic homelessness are usually structural conditions in people's lives—mental illness, trauma, debilitating health conditions, addiction, absence of qualifications or opportunities for employment, extreme poverty, and absence of sustaining personal connections. These problems do not go away just because someone is not documented as being homelessness in a given month; rather, they are drivers for the person's life trajectory.

To accurately identify high-cost homeless individuals, the triage tool must use multi-year information about individuals, assessing service encounters over a larger rather than narrower interval in their lives. It is likely that individuals with the highest 5 percent of costs move in and out of institutional care settings without being consistently documented as homeless. In addition, homeless individuals who are admitted to private hospitals, state psychiatric facilities, or incarcerated by the state correctional system would not be documented as homeless in county data systems.

Because of these data gaps, the homeless and persistently homeless status of individuals in the top 5 percent often is not evident, so we made the assumption that individuals documented as having been homeless who have ongoing public costs in the top 5 percent are likely to be persistently homeless.

Linked datasets provided information about factors that affect the outcome of interest: being a high-cost user next year. These included demographic variables such as age, gender, and ethnicity; clinical variables such as ICD-9 (International Classification of Diseases, Ninth Revision) medical

[4] The seven agencies participating in the record linkage were: the HUD Continuum of Care Board, Criminal Justice Information Control system of the Sheriff Department, Department of Alcohol and Drug Services, Emergency Management System, Mental Health Department, Social Services Agency, and Valley Medical Center.

diagnoses, and utilization variables for all service types from the current and previous year, including number of clinic or emergency room visits, number of hospitalizations and number of arrests, as well as the cost of services. The variables used in the model are listed in exhibit 1.

Exhibit 1

Averages of Model Variables for High-Cost and Other Homeless Persons (Validation Sample) (1 of 2)

Variable	High Cost (N = 5,726)	Other (N = 51,533)
Demographics (%)		
Age less than 18	5	10
Age 18–45	56	55
Age 46–65	36	31
Age 65+	3	4
Female	42	54
Criminal justice		
100+ days of probation in the last 2 years (%)	18	5
Arrested in last 2 years (%)	46	16
Jail booking in last 2 years (%)	23	9
Jail security classification of 3 or 4 (that is, high risk) this year (%)	10	1
Arrested for inebriation and released within 48 hours—this year (%)	8	1
Mean number of arrests this year	0.78	0.16
Mean number of days in jail this year	32.9	5.2
Health diagnoses		
Diagnosed with chronic medical condition; Chronic Condition Indicator for ICD-9-CM diagnosis codes by HCUP (%)	68	35
Medical encounter with diagnosis of adjustment reaction ICD-9 309 in last 2 years (%)	11	3
Medical encounter with diagnosis of heart disease ICD-9 401-429 in last 2 years (%)	6	2
Mean number of medical encounters with diagnosis of organ failure ICD-9 569-573, 576-578, 585-594, or 596 in last 2 years	0.6	0.1
Medical encounter with diagnosis of schizophrenia ICD-9 295 in last 2 years (%)	14	2
Mean number of medical encounters with diagnosis of neoplasm (ICD-9 140 to 239) in last 2 years	0.4	0.1
Medical encounter with diagnosis of “other ill-defined and unknown causes of morbidity and mortality” (ICD-9 799) in last 2 years (%)	17	4
Medical encounter with diagnosis of high-cost ICD-9 in last 2 years (%)	52	20
Health and emergency services		
EMS encounters this year (%)	30	7
EMS encounters last year (%)	29	7
Two or more EMS encounters in last 2 years (%)	12	1
Admitted as hospital inpatient via emergency unit admission or transfer from psychiatric facility in last 2 years (%)	20	4
Outpatient psychiatric emergency services or ambulatory surgery this year (%)	41	15
Mean number of hospital inpatient admissions this year	0.30	0.06
Mean number of hospital inpatient days in last 2 years	3.7	0.6
Non-inpatient (ER or clinic visit) health system encounter this year (%)	68	43
Mean number of non-inpatient (ER or clinic visits) encounters this year	6.2	2.3
11 or more non-inpatient (ER or clinic visits) health system encounters this year (%)	20	6

Exhibit 1

Averages of Model Variables for High-Cost and Other Homeless Persons (Validation Sample) (2 of 2)

Variable	High Cost (N = 5,726)	Other (N = 51,533)
Behavioral health		
Mean number of mental health outpatient days in the last 2 years	11.1	2.1
Two or more mental health outpatient visits in the last 2 years (%)	27	9
Mean number of mental health inpatient admissions this year	17.6	1.2
Two or more mental health inpatient admission in the last 2 years (%)	20	6
Substance abuse indicated by any recorded medical diagnosis or justice system charge (%)	61	31
Mean number of drug abuse and alcohol service encounters in the last 2 years	14.3	3.9
HUD-funded homeless services and county public assistance		
Chronic homeless flag in any HUD-funded homeless service provider record (%)	27	11
Public assistance benefits received this year (%)	46	40
Two or more months of food stamp payments received in the past 2 years (%)	47	44

EMS = Emergency Medical Services. ER = emergency room. HCUP = Healthcare Cost and Utilization Project. HUD = U.S. Department of Housing and Urban Development. ICD-9 = International Classification of Diseases, Ninth Revision.

The binary target variable indicated whether or not homeless persons were in the top 10 percent of high-cost users in 2009 (training cohort) and 2012 (validation cohort). In order to identify high-cost status, costs were summed across all service types and then ranked separately for the training and validation cohorts.

Analysis

The model predicts who is in the 10 percent of the homeless persons with highest public services costs in 2009, using data from 2007 and 2008. The model was validated by using 2010 and 2011 records to predict high-cost status in 2012. The sample size for the training and validation cohorts was 57,259 records. The target group was 5,726 homeless individuals who made up the 10 percent with the highest costs. It was important to test the model using data for 2010 to 2012 in order to assess its out-of-sample predictive power. Strong predictive power is often observed based on in-sample performance if the model over-fits the data. When that is the case, the model only effective for explaining the training data, and out-of-sample performance is very poor. Because a predictive model is intended to be applied to new data with unknown outcomes, validation is needed to assess a model's performance.

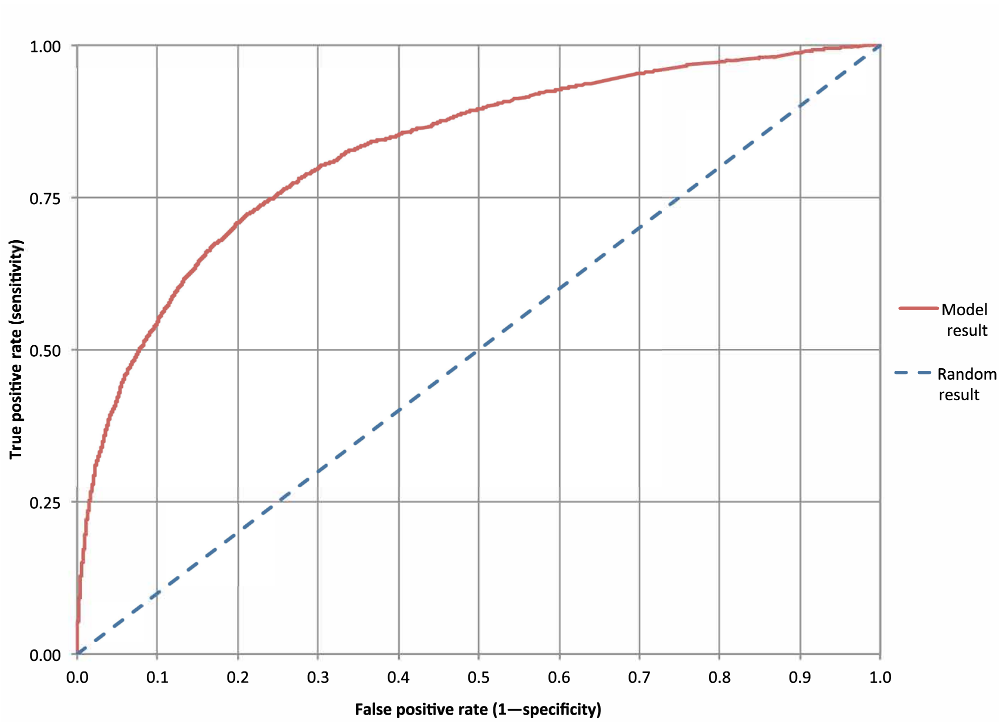
Model development was conducted in two stages. In the preprocessing stage, potential variables that might have an effect on becoming a high-cost user were identified based on earlier research and a series of F-tests (for categorical variables) and t-tests (for continuous variables). This step generated the first iteration of variable selection after eliminating redundant and irrelevant factors with p-values greater than 0.25. The initial set of selected variables was transformed and prepared for model development using several techniques such as binning continuous variables, clustering categorical variables, and generating binary and count variables. All variables were generated for the current and previous years, and a total of 256 input variables were selected to be included in the model development.

Several models for predicting high-cost users were developed and their performance was assessed using the SAS Enterprise Miner platform (Sarma, 2013; SAS, 2013). Several regression techniques were implemented to build models predicting the status of each person in the dataset as a high-cost user in the next year. We tested three techniques—logistic regression, least-angle regression, and decision tree models that are capable of explaining the classification or decision process, rather than using machine-learning algorithms that do not explain how given types of information are used to make predictions.

A comparison of the models' performance based on the receiver operating characteristic (ROC) curve led to selecting a logistic regression model as the champion model. The ROC curve shown in exhibit 2 plots the tradeoff between sensitivity or true positive rate (probability of true prediction) and specificity or false positive rate (probability of false prediction). The ROC curve is used to quantify how accurately a model can discriminate between two states—typically referred to as "event" and "nonevent"—or to compare two alternative models predicting the same event. In the final phase, this model was fine-tuned, introducing interactions between variables, testing the nonlinearity of variables and applying a sensitivity analysis to decrease the number of variables—particularly testing if current and previous year variables could be aggregated into a single variable without sacrificing the model's performance.

Exhibit 2

ROC Curve



ROC = receiver operating characteristic.

The final model was validated using the 2010–2012 cohort to assess the out-of-sample predictive power of the model. Sensitivity, specificity, positive predictive value (PPV), and accuracy measures, as well as the area ROC curve, were used to assess the out-of-sample model performance (Gonen, 2007).

The sensitivity statistic measures the proportion of high-cost homeless persons correctly identified by the model with high scores. It is also known as the true positive rate and reflects how well the model performs in capturing those homeless persons with high future costs. If the level is too low, a large number of high-cost homeless persons would not be provided with PSH.

The specificity statistic measures the proportion of not-high-cost homeless persons correctly identified by the model with low scores. If the level is too low, this is translated into to a high false positive rate (1-specificity), meaning a large number of homeless persons with low public costs would be provided with PSH.

The PPV statistic estimates the accuracy of the model by measuring the proportion of true positives (correctly classified high-cost homeless persons) within the population of all persons identified as high-cost persons. In other words, it is the probability that persons with a high score (above a defined cost threshold) truly are high-cost persons. Finally, the accuracy statistic measures the proportion of true positives and true negatives out of all persons.

The validated model was later utilized to estimate the potential costs and benefits of applying the model under several cutoff thresholds, using experience-based assumptions about costs of PSH and likely reduction in service use attributable to PSH placement.

Results

The final model had 38 variables with main effects out of 256 input variables tested and 11 variables with interactions. The descriptive values of model variables are shown in exhibit 1. The significance of the parameter estimates (*p*-values) and odds ratios are presented in exhibit 3. As shown in exhibit 1, high-cost homeless persons in Santa Clara County represent a higher proportion of males than the overall population that experienced homelessness, and are slightly older. Their rate of engagement in the criminal justice system is very high relative to the rest of the population. Almost half of them were arrested during the previous 2 years compared to only 16 percent for the rest of the population. Their average number of days in jail is more than six times greater than the rest of the population—32.9 days versus 5.2 days.

After testing 970 3-digit ICD-9 medical diagnoses, 43 diagnostic groups, and 18 body system diagnostic categories, the model retained six effective diagnosis codes or groups—adjustment reaction, organ failures, heart diseases, schizophrenia, neoplasm, and other ill-defined and unknown causes of morbidity and mortality. In addition, two other factors were included, which are the aggregations of chronic medical conditions and high-cost ICD-9. The high-cost homeless group shows much higher rates of encounters with these diagnoses whereas overall averages vary between 6 percent (heart diseases) and 68 percent (chronic medical condition). More than one-half of the high-cost group had been diagnosed with 1 or more of the 59 high-cost ICD-9s, while only a fifth of the lower-cost population had any of these diagnoses.

Exhibit 3

Logistic Regression Adjusted Odds Ratios and 95-Percent Confidence Limits for Predictor Variables (Validation Sample)

Variable	Odds Ratio	95-Percent Confidence Limits
Demographics (%)		
Age 18–45 versus less than 18*	1.21	1.06–1.38
Age 46–65 versus less than 18	0.98	0.85–1.13
Age 65+ versus less than 18***	0.88	0.69–1.14
Female versus male***	1.07	1.00–1.14
Female	42	54
Criminal justice		
100 or more days of probation in the last 2 years*	1.15	1.03–1.28
Arrested in last 2 years*	1.74	1.58–1.92
Jail booking in last 2 years*	1.14	1.04–1.26
Jail security classification of 3 or 4 (that is, high risk) this year*	1.63	1.41–1.89
Arrested for inebriation and released within 48 hours this year*	1.48	1.26–1.73
Number of arrests this year**	1.06	1.01–1.11
Number of days in jail this year*	1.007	1.005–1.009
Health diagnoses		
Diagnosed with chronic medical condition*	1.21	1.10–1.33
Diagnosed with adjustment reaction in last 2 years*	1.26	1.06–1.49
Diagnosed with heart disease in last 2 years*	1.41	1.15–1.72
Number of medical encounters with diagnosis of organ failure in last 2 years*	1.08	1.06–1.11
Diagnosed with schizophrenia in last 2 years**	1.23	1.03–1.46
Number of medical encounters with diagnosis of neoplasm in last 2 years*	1.05	1.03–1.07
Diagnosed with “other ill-defined and unknown causes of morbidity and mortality” in last 2 years **	1.28	1.05–1.58
Diagnosed with high-cost ICD-9 in last 2 years**	1.120	1.009–1.240
Health and emergency services		
EMS encounter this year*	1.27	1.14–1.41
EMS encounter last year*	1.26	1.14–1.40
Two or more EMS encounters in last 2 years*	1.34	1.12–1.60
Admitted as hospital inpatient via emergency unit admission in last 2 years*	1.35	1.19–1.54
Outpatient psychiatric emergency services or ambulatory surgery this year*	1.21	1.11–1.33
Number of hospital inpatient admissions this year*	1.16	1.09–1.25
Number of hospital inpatient days in last 2 years*	1.011	1.006–1.016
Non-inpatient (ER or clinic) health system encounter this year*	1.20	1.10–1.32
Mean number of non-inpatient (ER or clinic visits) encounters this year	6.2	2.3
11 or more non-inpatient (ER or clinic visits) health system encounters this year (%)	20	6
Number of non-inpatient (ER or clinic visits) encounters this year*	1.024	1.015–1.033
11+ non-inpatient (ER or clinic) health system encounters this year*	1.27	1.07–1.51
Behavioral health		
Number of mental health outpatient days in the last 2 years*	1.013	1.010–1.015
Two or more mental health outpatient visits in the last 2 years*	1.40	1.23–1.59
Number of mental health inpatient admissions this year*	1.002	1.002–1.003
Two or more mental health inpatient admission in the last 2 years*	1.28	1.08–1.51
Substance abuse indicated by any recorded medical diagnosis or justice system charge*	1.63	1.51–1.76
Number of drug abuse and alcohol service encounters in the last 2 years*	1.002	1.002–1.002
HUD-funded homeless services and county public assistance		
Chronic homeless flag in any HUD-funded homeless service provider record*	1.28	1.17–1.39
Public assistance benefits received in the current year*	1.36	1.18–1.57
Two or more months of food stamp payments received in the past 2 years*	0.68	0.59–0.79

* $p < .01$. ** $p < .05$. *** $p < .10$.

EMS = Emergency Medical Services. ER = emergency room. HUD = U.S. Department of Housing and Urban Development. ICD-9 = International Classification of Diseases, Ninth Revision.

The high-cost group also shows higher rates of engagement with health and emergency services. Group differences were large for EMS encounters (30 percent versus 7 percent), hospital inpatient admissions via emergency room admission or transfer from a psychiatric facility (20 percent versus 4 percent), and outpatient psychiatric emergency services or ambulatory surgery (41 percent versus 15 percent). The number of admissions and days of inpatient hospitalization and the number of outpatient encounters are also significantly higher for high-cost homeless persons.

Finally, behavioral health data show more frequent encounters for the high-cost group. Both mental health (inpatient and outpatient) and substance abuse service rates are higher. The prevalence of documented substance abuse, as indicated by any drug-related medical diagnosis or justice system charge, is twice as high for the high-cost group—61 percent versus 31 percent for the balance of the population. In contrast, the public assistance and homeless service participation rates differ only slightly.

Adjusted odds ratios presented exhibit 3 reflect the differences we observe from descriptive comparisons. Odds ratio for continuous variables are adjusted by controlling for all other variables. As a result, odds ratios for binary variables (for example, arrested or not) are generally higher than the odds ratios for continuous variables (for example, days in jail) and are interpreted differently. For example, the odds ratios show that persons who have been arrested in the past 2 years are 1.74 times more likely to be in the high-cost group than those who have not been arrested. On the other hand, the odds ratio for each additional arrest is only 1.06, increasing the likelihood (or odds) of being in the high-cost group by 6 percent.

Odds ratios analysis reveals that being arrested in the last 2 years, higher jail security and substance abuse are among the strongest binary predictors of becoming a high-cost homeless resident, followed by being arrested for inebriation and released within 48 hours, heart disease, two or more EMS encounters, being admitted as a hospital inpatient via the emergency room, two or more mental health outpatient visits, and receiving public assistance benefits. All factors included in the model increase the likelihood of becoming a high-cost homeless person with adjusted ratios in the range of 1.05 and 1.28, with the exception of receiving 2 or more months of food stamp payments, which has an odds ratio of 0.68, indicating that receiving food stamps benefits makes it less likely to be in the high-cost group. The adjusted odds ratios for continuous variables all have values ranging from 1.002 (number drug abuse and alcohol services encounters) to 1.16 (number of hospital admissions), and all increase the likelihood of becoming a high-cost homeless person.

General performance of the model was evaluated using *C*-statistic to assess the predictive ability of the model. The *C*-statistic (sometimes called the “concordance” statistic or *C*-index) is a measure of goodness of fit for binary outcomes in a logistic regression model. It gives the probability that a randomly selected subject who experienced an event (for example, became high-cost user) had a higher risk score than a subject who had not experienced the event. It is equal to the area under the ROC curve and has values ranging from 0.5 to 1.0.

The model achieved a very strong *C*-statistic: 0.83. *C*-statistic is the probability that predicting the outcome is better than chance. Models are typically considered reasonable when the *C*-statistic is higher than 0.7 and strong when C-statistic exceeds 0.8 (Hosmer and Lemeshow, 2000). Overall, the model predicts high-cost homeless persons with a very good fit.

Exhibit 4 shows the predictive performance of the model for different scenarios: the top 1, 5, and 10 percent and the top 1,000 homeless persons with the highest risk of becoming a high-cost service user. The predictive performance measures were defined previously in the methods section.

If the 2,864 persons in the top 5 percent at greatest risk of becoming high-cost homeless service users are followed, the achieved sensitivity and specificity are 32.6 and 97.3 percent, respectively. These values suggest very reasonable predictive power, indicating that the model picks up 33 percent of all high-cost service users and correctly identifies 97 percent of those who are not high-cost users. The PPV value of 51 percent and accuracy value of 92.3 percent for the top 5 percent are also very high. If we follow a subset within the top 5 percent, the 1,000 cases with the highest probability scores for being in the high-cost group (1.75 percent of all cases), we see even more accurate prediction outcomes. The model achieves a PPV result of 67 percent, meaning that out of 1,000 persons that the model identified as high-cost persons, two-thirds are true positives and the remaining one-third are false positives. PPV is an important measure for assessing the cost-effectiveness of the model.

Another measure of the effectiveness of a predictive model is the "lift," which is calculated as the ratio between the results obtained with and without the predictive model for all thresholds. Exhibit 5 illustrates the lift of the model, which is quite high for cases with a high probability of being in the high-cost group. For example, for the top 5 percent, the model generates a lift of 6.5. This means that model generates 6.5 times more correctly identified high-cost homeless persons (true positives) than random selection, which is presented as the baseline: a lift of 1 or 0. At slightly lower thresholds, such as the top 10 percent, lift drops to 4.7 because in order to capture more true positives, the model concurrently includes more false positives. Conversely, the number of false positives decreases as the probability of being in the high-cost group increases.

The most common way of assessing the predictive power of a model in the data mining literature is the area under the ROC curve. ROC shows the tradeoff between true positives (sensitivity) and false positives (1-specificity) at all possible thresholds. The ROC curve for the model is shown in exhibit 2. The accuracy of the model depends on how well it separates high-cost individuals from lower-cost individuals. Accuracy is measured by the AUC (Area Under the Curve, the ROC curve) or *C*-statistic. The model generated a fairly high AUC of 0.83, indicating an 83-percent probability that a randomly selected homeless person with high future costs will receive a higher model score

Exhibit 4

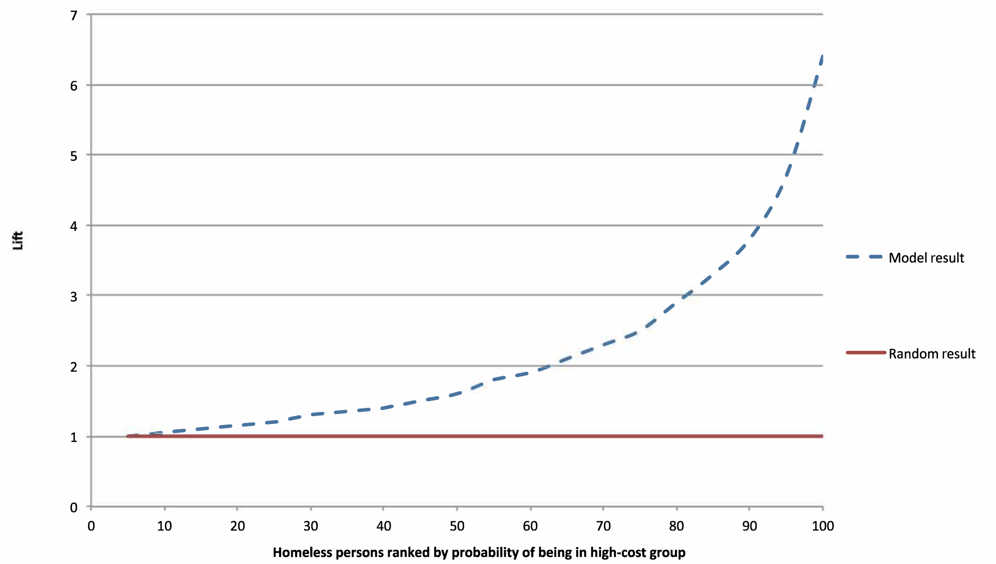
Predictive Performance of the Model

Measure	Top 1%	Top 5%	Top 10%	Top 1,000	Formula
Sensitivity (%)	9.3	32.6	47.7	14.9	True positive / (true positive + false negative)
Specificity (%)	99.7	97.3	93.2	99.4	True negative / (false positive + true negative)
PPV (%)	72.9	51.0	37.4	66.8	True positive / (true positive + false positive)
Accuracy (%)	92.6	92.3	89.5	92.7	(True positive + true negative) / number

PPV = positive predictive value.

Exhibit 5

Lift Chart



than a randomly selected homeless person without high future service costs. In the predictive analytics literature, models with AUC exceeding 0.8 are accepted as models with good predictive power, and AUC values below 0.7 indicate poor model performance.

Because the model provides a probability score ranging from 0 to 1, we have to select a cutoff score or a threshold, above which homeless persons will be offered PSH. Choice of a cutoff level introduces the tradeoff between the correct identification of high-cost service users and false alarm rates. The ROC curve illustrates this tradeoff between true positives—finding as many homeless persons as possible who would be high-cost service users next year—and false positives—decreasing potential cost savings by including homeless persons who would not be high-cost service users next year.

Business Scenario and Cost Savings

Although the performance of the triage tool presented in this article is very high in statistical terms, it is still necessary to translate this performance into a pragmatic business scenario, showing how the tool contributes to the efficiency of PSH programs by prioritizing the population to be housed. The tradeoff to be weighed in using the triage tool is between, on the one hand, using lower selection thresholds in order to find as many high-cost homeless individuals as possible but accepting a substantial number of lower-cost individuals as part of the mix, and, on the other hand, using higher selection thresholds to identify a smaller population in which a higher proportion of individuals will be high-cost service users. This tradeoff is critical to the efficiency of a PSH program as elaborated previously. The model is highly accurate in distinguishing high-cost from low-cost users, however it is still necessary to calibrate the cutoff level based on goals for saving costs by offering PSH to the targeted population. The following analysis explores the cost efficiency of providing PSH to targeted high-cost homeless persons under different cutoff levels.

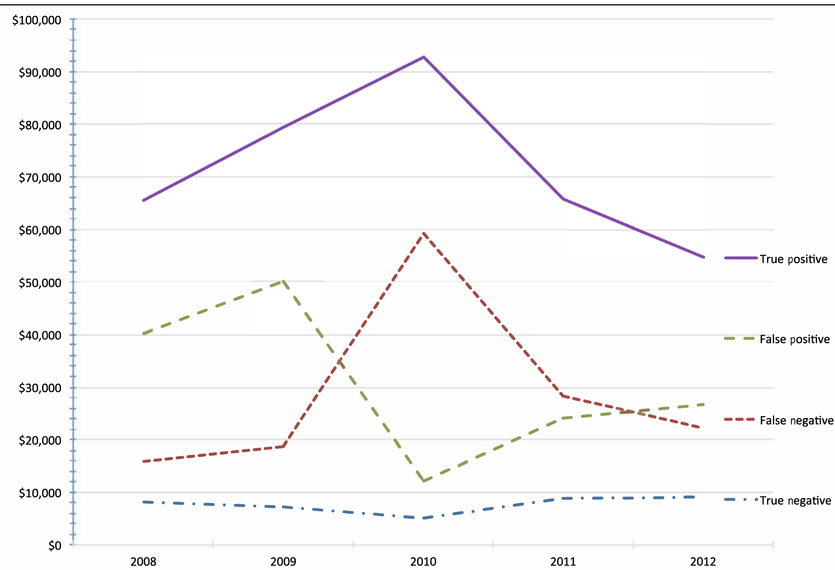
With 5 years of actual cost data, from 2008 through 2012, we used 2008 and 2009 data to produce probability scores for the likelihood of each individual being in the highest-cost group in 2010 and then track the accuracy and financial outcomes of these predictions over the next 2 years. Any placement decision has cost implications. If the homeless person predicted to be a high-cost user was correctly identified (true positive), the reduction in posthousing use of public services is likely to be roughly two-thirds. However, if the homeless person predicted to be a high-cost user was a false positive, then the expected cost savings would not be realized. The balance between the positive and negative savings generated by these two groups determines the efficiency of a PSH program.

One of the challenges the model must contend with is abrupt changes in costs in the scoring year—the year following the 2 years for which health conditions and service utilization are known. Some conditions are one-time events, resulting in costs that spike and then decline. Hence, the assessment of cost offsets should be done in the postplacement period, when the actual service utilization of true positives and false positives becomes evident. Some homeless persons who were true positives at the time of scoring year became low-cost users in subsequent years due to regression to the mean. On the other hand, some false positives that were predicted to be high-cost users but were low-cost users in the scoring year turned out to have higher costs in subsequent years.

These dynamics are shown in exhibit 6 for predictions of the top 5 percent. Looking at 2 years of post-scoring-year cost data (adjusted to 2014 U.S. dollars), the model successfully differentiates

Exhibit 6

Average Annual Costs for Triage Tool Prediction Groups



the highest cost cases from other cases, even though average costs decline because of regression to the mean. The low cost levels of true negatives verify the high specificity of the model. Another critical observation is that public costs for individuals experiencing homelessness vary significantly from one year to the next with important implications for the efficiency measure. False positives represent homeless persons with high service utilization prior to the scoring year of 2010, which led to high probability scores. However, in 2010, their service costs were low, making them false positives. On the other hand, their postprediction trend is positive, more than doubling between 2010 and 2012. If a person was predicted at the top 5 percent and had no service utilization at 2 years post scoring year, the person was labeled as false positive. If he or she was not predicted at the top 5 percent, the person was labeled as true negative, because he or she remained a low-cost user after the scoring year.

Note also that false negatives, the group with low service utilization prior to 2010 and high costs in 2010, the scoring year, typically had one-time cost spikes. Their long-term trend is negative and subsequent to the scoring year their cost levels declined substantially. Hence, omitting them as high-cost users contributes to the efficiency of the program significantly as presented below exhibit 6 suggests that cost savings should be assessed not at the year of scoring but rather in the postscoring years in order to capture the long-term service utilization of scored individuals.

The triage tool works to assign high scores to high-cost users, but different probability cutoff levels will exhibit different proportions of true positives with expected savings and false positives with no expected cost savings. Our estimation of net savings at different cutoff levels is based on the estimated cost savings for true positives after taking into account the housing and service costs for false positives. The results are sensitive to the probability score threshold, cost of housing, and the rate of anticipated reduction in service utilization and costs following placement in housing. As the probability score threshold increases, the ratio of true positives to false positives also increases, resulting in increased savings.

This analysis looks at financial outcomes based on two probability score thresholds, 0.37 and 0.53, for the predicted probability of having high costs in 2010, based on 2008 and 2009 information. The 0.37 cutoff level identifies approximately 5 percent of the test population as high-cost users. The 0.53 cutoff level identifies the top 1,000 high-probability service users in our test population. A different probability cutoff can be selected based on the requirements of specific initiatives to address homelessness. If the goal is to house a larger number of high-cost homeless persons, lower cutoff levels may be selected, resulting in lower savings per person. On the other hand, if the supply of housing is limited and a smaller number of high-cost homeless persons can be housed, than a higher cutoff level may be selected, resulting in higher savings per person.

It is assumed that the annual cost of PSH is $17,000 per person per year, based on rent subsidy and supportive service costs in Los Angeles. We used Los Angeles data for housing costs and posthousing cost savings because, at the time of our study, Santa Clara County did not have enough high-cost individuals who had been housed for a long enough interval to produce comparable data. This high-side estimate of housing costs is based on $11,000 annually for rental subsidy, including first-year costs for temporary housing and benefits advocacy, and $6,000 annually for supportive services. Actual costs may be lower based on the level of subsidies built into different affordable housing projects and the level of long-term supportive services needed by tenants after they are stabilized in housing.

The posthousing reduction in service costs is assumed to be 68 percent for homeless persons in the 10th decile based on a study from Los Angeles (Economic Roundtable, 2009). Most other studies estimate service cost reductions for homeless persons in PSH for the whole population, rather than the top decile (Culhane, 2008; Culhane and Byrne, 2010). It is also assumed that there will not be any cost reduction for false positives—individuals below the 10th decile. This is a conservative assumption because an earlier study also found posthousing cost reductions among individuals in the 5th through 9th cost deciles (Economic Roundtable, 2011). However for purposes of the cost estimates shown here, net savings are -$17,000 for cost groups below the 10th decile because no cost savings are applied to them.

Exhibit 7 presents estimated cost savings for 2011 for the two selected cutoff levels (0.37 and 0.53). Posthousing costs are calculated as 32 percent of homeless costs for individuals in the 10th cost decile, and then $17,000 is added for each person in the group to cover the cost of housing and supportive services. Net savings are calculated by subtracting estimated posthousing costs from actual homeless costs for the year. All analysis was conducted in 2014 prices. Since actual costs in 2011 and 2012 were used, regression to the mean, that is, the tendency of extreme outcomes to be closer to the average when measured a second time, has been incorporated into the estimates.

Cost differences were estimated for four probability-cost groups, which each show different cost dynamics. If a score was above the selected cutoff (0.37 or 0.53) and 2010 costs were in the top decile, the record is a true positive. However, in subsequent years, true positives in 2010 may remain high-cost or become low-cost service users. The long-term cost status of individuals was

Exhibit 7

Cost Savings for 2011 at the Cutoff Levels of 0.37 and 0.53

Status	2010 Costs (Prediction Year) ($)	2011 Costs (1 Year After Prediction) ($)	2011 Cost Savings ($)	2011 Net Savings ($)	2011 Total Savings ($)	Number of Cases
Cutoff level: 0.37						
True positives—low-cost users	90,989	10,932	0	– 17,000	– 4,335,000	255
True positives—high-cost users	93,196	83,661	56,889	39,889	30,635,068	768
False positives—low-cost users	11,444	8,511	0	– 17,000	– 8,823,000	519
False positives—high-cost users	13,029	46,551	31,655	14,655	5,085,204	347
Total / average				11,944	22,562,272	1,889
Cutoff level: 0.53						
True positives—low-cost users	111,580	11,496	0	– 17,000	– 2,074,000	122
True positives—high-cost users	96,892	86,947	59,124	42,124	22,367,823	531
False positives—low-cost users	12,427	8,829	0	– 17,000	– 3,094,000	182
False positives—high-cost users	13,579	43,560	29,621	12,621	2,082,432	165
Total / average				19,282	19,282,255	1,000

evaluated based on their actual cost rankings in 2011 or 2012. If they were in the top decile in 2011 or 2012, they were identified as long-term high-cost users. Otherwise, they were identified as low-cost users.

If a score was above the selected cutoff (0.37 or 0.53) and 2010 costs were not in the top decile, the record is a false positive. False positives may also become high- or low-cost service users in the future. We tested this possibility by observing actual costs in 2011 and 2012 and identifying cases that moved into the true positive cost category. Exhibit 7 shows that, at the 0.37 cutoff level, out of the 1,123 individuals who were true positives, 255 became low-cost users in 2011. This cost shift was more than offset by 347 false positives that turned out to be high-cost users in 2011. In sum, out of 1,889 individuals, 1,115 (60 percent) were high-cost users in 2011.

If the 5 percent (0.37 cutoff level) with the highest probability of being high-cost service users were housed permanently with supportive services, savings of more than $22 million were estimated in 2011. Even though 40 percent of individuals were low-cost users in 2011 and would not be generating any cost savings, the net savings from the remaining 60 percent shows the feasibility of the intervention. The analysis shows a cost reduction of almost $12,000 per housed homeless person for the top 5 percent of the population identified by the triage tool as having the greatest probability of high future costs.

The results are even more positive when a higher cutoff level is selected, because the accuracy of the tool in predicting high-cost users improves as the probability level increases. The 2011 cost analysis for 1,000 persons in the test population with the highest probability scores, scores at or above 0.53, shows that almost two-thirds (653 individuals) were true positives. Evaluating actual costs in 2011, it is observed that 122 of them became low-cost users, whereas more than four-fifths (531) remained high-cost users. In addition, 165 false positives turned out to be high-cost users in 2011. In sum, out of 1,000 individuals, 696 (70 percent) were high-cost users in 2011. As expected, the feasibility of the intervention is higher at the 0.53 threshold than at the 0.37 threshold, with an estimated cost reduction for this group of more than $19,000 per person in 2011.

A separate analysis estimated savings in 2012 for both cutoff levels. Because lower cost levels were observed in 2012 due to the regression to the mean, lower cost savings were estimated. At the 0.37 level, cost savings were estimated to be almost $16 million, which corresponds to more than $8,000 per housed individual. At the 0.53 level, savings per individual were estimated to be $16,000, with cumulative savings for 2011 and 2012 estimated to exceed $35 million. Over the 2 years of postprediction data that we have for Santa Clara County, we see a year-to-year decline in actual costs for individuals with a high probability of having high costs. However, this may be the first phase of a longer-term cost cycle in which costs begin to increase again. This scenario is plausible considering that most individuals in this population have serious medical and mental health disorders that are likely to become more acute as they age. Indications of a longer-term cycle in which costs decline and then increase were found in an earlier cost study in Los Angeles (Economic Roundtable, 2009).

As noted previously, our cost savings analysis assumed that the annual cost of PSH is $17,000 per person per year and that the posthousing reduction in service costs is 68 percent for homeless persons in the 10th decile. Because both of these assumptions are made based on data and recent studies from Los Angeles, a separate sensitivity analysis was carried out to see how total net cost savings estimates change if these cost assumptions change. The analysis showed that at the 0.37 cutoff level, the break-even point is reached when the annual cost of PSH is $29,000 or the posthousing reduction in service costs is 40 percent. These are the highest annual cost of PSH and the lowest percentage of service cost reduction that still yield net cost savings.

If instead of cost savings as a goal, a community seeks to break even against current or projected costs, a probability threshold of 0.20 is estimated to produce "break-even" cost outcomes, with cost savings from reduced service use equal to the cost of housing and services. An estimated 70 percent of the population captured at this probability threshold is chronically homeless, and they represent an estimated 21 percent of all individuals who are chronically homeless in a given year.

Discussion

This study is the first attempt in Santa Clara County and one of the first studies to develop and validate a predictive model for identifying homeless persons who are likely to become high-cost users of public service. This model was developed using an integrated database built by linking seven agencies' administrative records, which provided information on risk factors such as demographics, clinical variables, and service utilization variables for the current and previous years as well as cost of service data. The cost study that was used to develop the triage tool provided key evidence supporting Measure A, a $950 million affordable housing bond measure approved by voters in 2016.

The model is particularly strong when using high probability cutoff levels, generating small numbers of false positives and high numbers of true positives. For the top 1,000 high-cost users predicted by the model, two-thirds of them are true positives. A key strength of this study is that it assessed the overall effectiveness of predictions made by the tool, looking at costs over the 3 years following the 2 years that were the source of data used to make the prediction. This assessment showed that many false positives became high-cost or close-to-high-cost users in the second year after the prediction. In addition, a majority of the false negatives were actually true negatives over the next 2 years because their high-cost level in the scoring year represented a one-time cost spike. One of the challenges the model must contend with is abrupt changes in costs from one year to the next. Some conditions are one-time events, resulting in costs that spike and then decline. The tool performed very well by giving low scores to homeless persons with one-time cost spikes.

Another key strength of the study is information it provided for identifying distinctive attributes of high-cost individuals. Individuals in this group are the most likely to be diagnosed with a mental disorder, in particular, a disorder that takes the form of a psychosis, and a psychosis that takes the form of schizophrenia. They are also the most likely to be given a maximum or high-medium security jail classification because of the safety risk they are perceived to present. They are the most likely to have been continuously homeless for 3 years. They are most likely to be diagnosed with a skin disease such as cellulitis or an endocrine disease such as diabetes. They are most likely to be tri-morbid—diagnosed with a mental disorder, a chronic medical condition and to abuse drugs or alcohol. Demographically they are most likely to be male and to be in the middle of their lives—35 to 44 years old. Also, they are most likely to frequent users of hospital emergency rooms and inpatient beds, emergency psychiatric facilities, mental health inpatient facilities, and to be incarcerated in a jail mental health cell block.

This composite profile can help hospital and jail discharge planners and homeless service providers identify high-cost individuals. However, significant diversity is in the demographic attributes and types of crisis services needed by individuals in this population. The triage tool weighs the likely cost impact of each individual's characteristics and uses this information to identify subgroups that fall outside this profile. For example, young women with acute mental illnesses and endocrine diseases who have ongoing high costs even though they are not substance abusers or involved in the justice system.

We further validated the model by developing a business analysis to assess its cost effectiveness. With 0.37 selected as the optimal cutoff level, which identifies the highest-cost 5 percent of the population that experienced homelessness over a 6-year period as the target group, the model assessed cost savings by comparing total housing and service costs ($17,000 annually) with the estimated 68 percent cost savings for true positives—those correctly identified as high-cost service users. The results confirmed that anticipated cost savings from true positives far exceed the total costs of housing, yielding net savings of $20,000 per person over the next 2 years, after the total population with a probability score of 0.37 or higher enters PSH. Using 0.53 as the minimum probability threshold for the target group, the estimated annual savings are $32,000 per person, after paying for housing and supportive services. On the other hand, using 0.20 as the probability threshold, we achieve break-even financial results, with the cost of providing housing and supportive services fully offsetting cost savings from reduced service use.

The optimal cutoff is not simply an empirical decision. In the context of PSH, it depends on the number of people who can be housed in available housing. However, in the context of a long-term strategy to address homelessness, the tradeoff between costs and savings in the population needing housing provides evidence that jurisdictions can use to validate local policy initiatives, such as affordable housing bond measures to expand the inventory of available housing.

It is often argued that the feasibility of prevention services, such as PSH, would not be attained without a strategy of balancing the costs with some degree of cost offsets. One of the most significant strengths of this study is its strong performance in identifying homeless persons with a high probability of having high ongoing public costs that will substantially exceed the cost of PSH.

The predictive performance of the Silicon Valley Triage Tool was compared to the performance of two earlier triage tools developed in Los Angeles by running all of the models on records of homeless persons from both Los Angeles and Santa Clara Counties. The tools were assessed based on the proportion of high-cost homeless persons correctly identified by each model and the proportion of persons predicted to be high-cost homeless who truly were high-cost persons. The Silicon Valley tool demonstrated comparable or higher accuracy when run on Los Angeles data and much higher accuracy when applied to the Santa Clara data. This comparison verifies that the Silicon Valley tool demonstrates strong predictive performance in multiple metropolitan regions.

Limitations

This analysis and the model developed in this study are also subject to some limitations that need to be acknowledged, and most of these limitations are inherent to analysis involving administrative datasets. Our study is limited by the usual shortcomings of research based on linked administrative records, including errors in the underlying data sources, such as missing data and data entry errors. Matching inaccuracies prevented the use of the full homeless population for the analysis. The tool was developed using data for roughly 55 percent of the population that experienced homelessness, 57,259 persons. These were individuals with at least one record linked to an agency during our 6-year study window from 2007 through 2012. Since administrative databases usually are not designed to collect data for research, information about some critical risk factors is often missing. For example, in developing this tool, we did not have access to data about income and employment. Moreover, some service costs were missing for some years and had to be estimated. For some services, when individual-level costs were not available, average costs per unit of service were used.

Another shortcoming related to the use of administrative data is incomplete and sometimes inaccurate information about the timing of homeless episodes. Because complete information about the duration of homelessness was not available, the study population was assumed to be either homeless or at risk of homelessness while predicting high-cost users, assuming that individuals would use more services when they were experiencing homelessness. In addition, the administrative datasets did not show the mobility of homeless individuals in and out of the county, which would impact their utilization of services in county facilities.

The business scenario that estimated cost savings was also subject to some limitations. First, it assumed that PSH costs $17,000 a year, which needs to be verified when the county has a larger body of postsupportive housing cost data. Second, because posthousing costs of homeless persons were not available for this study, cost offsets were based on a saving factor of 68 percent, which was derived from an earlier study conducted in Los Angeles. Actual cost savings may be different after the implementation of the program. On the other hand, service reductions measured here represent a conservative assessment of the impact of the PSH on service use and costs because it was assumed that homeless persons with costs below the 10th decile would not experience any service reductions after being housed, so that PSH costs were not adjusted with any cost offsets for this group.

Finally, the Silicon Valley Tool is a system-based tool; that is, it requires detailed healthcare and justice system information about each individual that is available only from those institutional systems. This includes medical diagnoses, accurate details of encounters with healthcare providers, and details about stints of incarceration. Cooperation of both healthcare and justice system agencies is necessary to protect the privacy of personal information while providing the data required for the tool. Santa Clara County agencies agreed to authorize a research unit in the Behavioral Health Services Department to link records across county agencies and then to de-identify the linked records so that they could be used by the Economic Roundtable to develop this triage tool.

Because of the level of effort required to obtain and integrate the necessary data, the most efficient use of the tool is for regular, ongoing system-wide screening of linked records rather than screening clients individually. By predicting how likely each person in the entire identified population of homeless resident is to have high future costs, it is possible to prioritize individuals for access to the scarce supply of PSH. For example, targeted individuals can be flagged in client databases so that housing can be offered to them the next time they seek services.

The Silicon Valley Tool can also be used to screen cases individually. A version of the tool for individual screening in Excel format as well as software code for screening entire client databases can be downloaded at https://economicrt.org/publication/silicon-valley-triage-tool/.

Because the tool does not correctly identify all high-cost individuals, the screening process for either individuals or groups should include an option to override the triage tool probability score based on the clinical judgment of healthcare professionals. For example, if a patient has recently been diagnosed with a high-cost, chronic medical condition, this would warrant overriding a negative result from the triage tool and including the patient in the high-cost group that receives access to PSH. Allowing overrides permits service providers to adapt to changing populations and conditions and to be responsive to unique circumstances.

The tool also has practical value for identifying patients served by health plans and private hospitals who have high ongoing costs, and whose health outcomes will improve and costs decrease if they are housed. Local government safety net resources can be augmented through collaborative care for frequent users who are also served by private hospitals.

Using the triage tool raises the broader ethical issue of making decisions about who gets into housing and who is left out. We see the tool as an interim means of prioritizing need in the context of an inadequate supply of affordable housing and insufficient human service interventions for reducing the flow of people into chronic homelessness. In this context, the tool prioritizes individuals based on public costs, which reflect frequency of service-intensive crises, and are closely linked to (but not identical with) level of distress. Use of the triage tool may be the approach that houses the greatest number of people because public agencies achieve the highest level of cost avoidance by housing high-cost individuals, opening the possibility of using those savings to pay for other crucial services.

Conclusion and Future Research

Needs within the homeless population vary significantly. Although the Silicon Valley Triage Tool is effective for prioritizing access to PSH for the small number of high-cost individuals who account for the majority of public costs, other tools are needed to target services for less disabled segments of the population. Less expensive interventions may be effective for individuals with less acute needs. This includes preventive care for children who have experienced homelessness, integrated outpatient healthcare, readily available and effective behavioral and mental health services, temporary affordable housing, and employment services. Without effective early intervention, the risk that individuals will become chronically homeless and that their problems will worsen to the extent that they become high-cost homeless is real.

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Authors

Halil Toros is statistical analytics consultant at the Economic Roundtable.

Daniel Flaming is President of the Economic Roundtable.

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Scale in Housing Policy: A Case Study of the Potential of Small Area Fair Market Rents

Matthew Palm
University of Melbourne

Abstract

The U.S. Department of Housing and Urban Development (HUD) caps subsidies for Section 8 housing vouchers using limits known as the Fair Market Rents (FMRs). HUD recently implemented Small Area Fair Market Rents (SAFMRs), based on ZIP Code-level rents, to improve options for voucher recipients in high-opportunity areas. I use a proprietary dataset of for-rent listings to test the ways in which SAFMRs would change the number of listings below FMR across five California HUD metropolitan FMR areas—Oakland-Fremont, Sacramento--Roseville--Arden-Arcade, San Diego-Carlsbad, San Francisco, and San Jose-Sunnyvale, Santa Clara. I examine local housing authorities' concerns regarding the SAFMRs. I find the SAFMRs will increase the number of listings below FMR in high-opportunity neighborhoods across each area studied except San Francisco. I confirm Oakland housing authorities' concerns that the SAFMRs would reduce the number of units below FMR in areas with rapidly rising rents. I find that Sacramento and San Diego may benefit most from the SAFMRs among those studied. These findings validate HUD's criteria for identifying areas in which to implement the SAFMRs, as Sacramento and San Diego are also the only two areas among the case studies in this article that HUD initially approved for SAFMRs implementation. The SAFMRs highlight the importance of geographic scale in housing policy implementation.

Introduction

In select metropolitan areas, HUD recently implemented a new way of defining Fair Market Rent (FMR), the subsidy limits for Section 8 housing vouchers.[1] This change, called the Small Area

[1] "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." Final Rule. 24 CFR Parts 888, 982, 983, and 985. *Federal Register* 81 (221) November 16, 2016.

Fair Market Rent (SAFMR), shrinks the geographic scale at which HUD calculates these voucher maximums from the metropolitan scale, known as the HUD metro FMR area, to the smaller ZIP Code-related geography. HUD implemented this rule to encourage voucher recipients to relocate into high-opportunity areas. Recent research finds that children who grow up in high-opportunity communities are more likely to experience upward social mobility (Chetty, Hendren, and Katz, 2016). The results of an SAFMR pilot program in Texas suggest that this policy scale change does improve voucher holders' locations (Collinson and Ganong, 2013). However, advocates and public housing authorities (PHAs) in some areas objected to the SAFMRs, arguing the American Community Survey (ACS) data used to define FMRs did not keep pace with rapidly rising rents. They also noted the SAFMRs did not consider the lack of vacancies in some markets, or the ways SAFMRs could reduce housing options for residents in gentrifying communities (Johnson, 2016b; Levin, 2016).

In this study, I examine two aspects of the SAFMRs. First, I test the ability of SAFMRs to increase the number of listings below the voucher payment limits (henceforth, "below FMR") in high-opportunity neighborhoods. Second, I test the concerns of some PHAs regarding the way in which SAFMRs may exacerbate the impacts of rising rents and reduce the number of below-FMR units in markets with tight vacancy rates. I utilize a proprietary database of for-rent listings covering five HUD metropolitan FMR areas in California—Oakland-Fremont (henceforth, Oakland), Sacramento--Roseville--Arden-Arcade (Sacramento), San Diego-Carlsbad (San Diego), San Francisco, and San Jose-Sunnyvale-Santa Clara (San Jose)—from 2012 and 2013 to model these potential impacts of the SAFMR. As some SAFMR critics' concerns involve rapidly rising rents, I also draw on data from the same proprietary source for 2011 and 2014–2015 to contextualize my results within each area's market trends. Because the use of web-based rental listings to study housing affordability is new, I also present a set of results comparing my analysis with those of the only other study to examine FMRs using web-based rental listings, conducted by Boeing and Waddell (Boeing and Waddell, 2016).

I find that the SAFMRs would increase the share of below-FMR listings in high-opportunity areas in four of the five HUD metropolitan FMR areas studied, the exception being San Francisco. I note that San Francisco's unique results are a function of rents increasing faster than the SAFMRs in that area's expensive ZIP Codes. I also identify a pattern unique to Oakland—the SAFMRs would exacerbate the loss of below-FMR units in lower rent ZIP Codes where rents are significantly increasing, reconfirming local PHAs' concerns (Johnson, 2016b). I fail to find a relationship between ZIP Code vacancy rates and the potential impact of the SAFMRs, suggesting the SAFMRs may not reduce the overall share of units below FMR.

This article contains five sections. I begin with a background to provide a more detailed explanation of FMRs, SAFMRs, and theoretical motivations behind the SAFMR approach. In the following section, a literature review examines the many obstacles facing voucher recipients, noting a lack of attention among scholars for the role that market rents play in limiting voucher holders' choices. I also highlight the data limitations of the few studies that do consider market constraints. I then detail local agencies' concerns with the SAFMRs and present several hypotheses based on this review. A data section and methods section follows in which I note the limitations of rental listings data. My results and conclusions highlight the implications of the SAFMRs for each of the metropolitan areas studied in this article.

Background

Vouchers enable participating households to pay only 30 percent of their income on rent, with the remaining rent subsidized by the federal government up to FMR limits (HUD, 2017a). HUD calculates FMRs for thousands of geographies known as HUD metropolitan FMR areas, geographies that can encompass between 50,000 and several million residents. HUD began using the ACS to measure FMRs after a report from the U.S. Government Accountability Office called for greater transparency and consistency in FMR implementation. The report detailed the need for a cost-effective approach to calculating FMRs that would be consistent across jurisdictions and over time and transparent enough that concerned local housing authorities could replicate and thus verify proposed FMRs (GAO, 2005). HUD responded to the report by adopting the ACS for its FMR calculations and by developing a completely open-access FMR documentation system available online (HUD, 2017a).

To calculate the FMRs, HUD starts by estimating the 40th percentile of the distribution of gross rents in each metropolitan FMR area, by number of bedrooms, using the latest available ACS data (HUD, 2017b). Gross rents include both the contracted rent for housing and the utilities paid by the household, meaning that HUD intends for FMRs to cover utilities and rent. HUD relies on the latest 5-year rolling sample of the ACS to produce these estimates (U.S. Census Bureau, 2016a). If recent movers in the ACS report significantly higher rents than the 40th percentile, then HUD adjusts the 40th percentile rent proportionally upward. HUD uses the latest 1-year sample of the ACS to make these recent mover adjustments, bringing the data inputs closer to the time of policy application.

HUD must publicly post FMRs for thousands of jurisdictions several months prior to the year of their implementation to provide time for PHAs and other stakeholders to comment on the proposed limits. HUD usually posts the FMRs in September of the prior year (NLIHC, 2016a). By that time, however, the latest ACS data available are usually 2 years old. To account for this lag, HUD applies trend and inflation factors to the initial ACS-derived limits. Although this method accounts for time factors, spatial challenges remain. The traditional FMRs are frequently insensitive to inter-neighborhood variations in rental market conditions. HUD's calculation of the FMRs covering large geographies creates a mismatch between local markets and regional statutory voucher limits.

The SAFMRs address this problem. To calculate the SAFMRs, HUD first calculates a ratio—the median rent of a ZIP Code more than the median rent of its respective metropolitan statistical area (MSA). Suppose this ratio equals 110 percent for a given ZIP Code, because this ZIP Code is 10 percent more expensive than its overall MSA. HUD multiplies this ratio to the existing FMRs to calculate the SAFMR for that specific ZIP Code. This SAFMR now better reflects the rental market in this more expensive ZIP Code. Voucher recipients in that ZIP Code can now rent units 10 percent more expensive than those they could previously rent. HUD caps SAFMRs at 150 percent of their respective FMRs.

Geographic theory suggests this change should improve the ability of housing voucher recipients to disperse evenly across metropolitan areas. Tobler's First Law of Geography holds that near things are more related than far things (Miller, 2004). Housing is no exception. Rental and land markets are highly autocorrelated across space, with spatially oriented approaches like geographic fixed effects and geographically weighted regression often better predicting rents and home prices than nonspatial statistical techniques in multiple studies (Löchl and Axhausen, 2010; McCord et al., 2014; Tu, Sun, and Yu, 2007). This spatial autocorrelation suggests that the rents of a unit's neighbors can more easily predict that unit's rent than similar units much farther away. The SAFMRs embodies this principle.

HUD recently rescinded the mandatory implementation of the SAFMRs in response to mounting uncertainty about its programmatic costs (NLIHC, 2017). Advocates successfully challenged that decision in court, and it appears the SAFMRs will take effect (Cohen, 2018).[2] Some critics argued that the SAFMRs would reduce the number of households supported by vouchers, because it would raise the cost of the program without providing additional revenue to offset those costs (NAHB, 2017). When considering the FMR, HUD must also contend with the fact that "flat rents" for public housing tenants are also derived from the FMR (HUD, 2015). Flat rents are alternative affordable rents for public housing tenants that are higher than income-based rents but do not rise if the tenants' income rises. Some jurisdictions have implemented flat rents as an incentive for public housing tenants to find employment (SAMHSA, 2016). The link between the flat rent and FMRs creates a separate set of stakeholders, public housing tenants in flat rent jurisdictions who would be adversely impacted by rising FMRs.

Unfortunately, rental prices and FMRs are only one of many factors constraining voucher holder's location choices. The following literature review details these challenges.

Literature Review

Researchers first identified the failure of housing vouchers to induce recipients to move into high-opportunity neighborhoods early in the life of the program (Newman and Schnare, 1997). More recent work confirms that this pattern continues in voucher location outcomes (Galvez, 2011), with one study suggesting voucher holders actually began reconcentrating in low-opportunity areas in the past decade (Metzger, 2014).

The literature identifies several causes of these patterns. One recent review of the evidence finds voucher holders lack support in the process of searching for housing, face lawful landlord discrimination against the use of vouchers as a source of income, and have limited social networks that constrain their capacity to relocate (Galvez, 2010). Perhaps as a result of these factors, voucher recipients who move involuntarily generally move to within 3 miles of their prior homes (Goetz and Chapple, 2010; Kleit and Galvez, 2011). The factors identified by Galvez (2010) may also help explain the reasons voucher holders who do relocate to the suburbs sometimes do so by renting in affordable housing sites built by the country's supply-side housing programs, such as the Low-Income Housing Tax Credit Program (Wang and Varady, 2005). If social networks are linked to one's race and class, the social network factor may explain the persistently unequal locational outcomes between White and non-White voucher recipients, although these trends appear to have improved slightly (McClure, Schwartz, and Taghavi, 2014). Reliance on public transportation may also limit the relocation options of voucher recipients who lack vehicles (Ruel et al., 2013).

[2] As of January 30, 2018.

The culmination of these challenges is so severe that even offering voucher recipients additional financial support if they agree to "move to opportunity" often fails to induce relocations into areas of higher opportunity (Schwartz, Mihaly, and Gala, 2016).

This body of literature largely ignores the role of market forces, or the role of the FMRs, in curtailing voucher recipients' ability to penetrate higher opportunity neighborhoods. This literature offers no obvious insight into the ramifications of the SAFMRs, except to suggest it does not directly address many of the challenges voucher recipients face. However, the literature does demonstrate that even if the SAFMRs make voucher use in high-opportunity neighborhoods a financial possibility for participating families, they may not make it more likely to happen. This pattern will be particularly evident in states where source-of-income discrimination is legal, and landlords can lawfully refuse to rent to voucher holders (Tighe, Hatch, and Mead, 2016). As I discuss in the next section, the thin body of work that tackles market constraints relies on data that may be insufficient for properly assessing the role of market constraints.

Data Challenges in Unpacking Market Constraints

Researchers studying FMRs consistently find units renting below FMRs exist in nearly every census block group across the United States (McClure, 2014; McClure, Schwartz, and Taghavi, 2014). McClure also finds, however, that units below statutory FMRs are disproportionately in higher poverty neighborhoods. HUD references this finding in its rationale for the SAFMRs.[3]

Studies relying on the ACS, or long-form census, must contend with the challenge of data lag. How relevant and representative can years-old data be to voucher recipients who face rental markets in constant flux? Little research considers the means by which vacancies, seasonal factors, and rapidly changing market conditions might bias ACS-reliant analysis. Rapidly changing markets matter greatly in areas with rent control. For example, a unit captured in the ACS data or long-form census by McClure (2014) may be voucher accessible, simply because rent control applies and the rent observed is far lower than it would be if the unit returned to the market. Some researchers have attempted to measure the impact of market restraints on voucher relocation decisions with ACS median rents (Kleit and Galvez, 2011). This approach includes an additional drawback. The ACS tract-level median must represent market forces for units of all sizes, when in fact the FMRs vary based on the number of bedrooms, and these variations can fluctuate by metropolitan area.

Several papers have addressed the challenge of estimating the effect of the FMR by selecting a unit size with an FMR threshold that closely mirrors an ACS cross tabulation. For example, in a case study area where the FMR for a two-bedroom was $979, researchers used ACS tabulations that count the number of units in a tract renting up to $999 a month as a proxy for below-FMR counts (Cunningham and Droesch, 2005; Horn, Ellen, and Schwartz, 2014). This improvement comes with the trade-off of smaller ACS samples representing market conditions in these tracts. This method relies not on the small ACS tract samples but on even smaller sub-samples within them. Unfortunately, the switch from a long-form census to the 5-year ACS wave complicates this approach for the future, as 5-year wave estimates are highly unstable and potentially biased across space at the tract scale (Bazuin and Fraser, 2013; Folch et al., 2014).

[3] Final rule.

One recent study offers insights by examining the FMR eligibility of rental listings posted on Craigslist (Boeing and Waddell, 2016). Compared with previous studies and HUD expectations, Boeing and Waddell found fewer below-FMR units in many of the country's most expensive markets. This significant difference suggests the need for further analysis of market constraints utilizing different kinds of data. Market studies conducted in Oakland, for example, led to significant upward revisions in FMRs there (Johnson, 2016a). Those findings, placed alongside Boeing and Waddell's estimates, imply that Craigslist may be more accurate than the ACS in capturing present market conditions.

Another recent study by Geyer (2017) also models the role of the market in explaining vouchers recipients' locational patterns. Geyer relies on listings of below-FMR units to build a model of voucher holders' residential location choices. She uses this model to predict the way various policy changes will affect the locations of voucher recipients. She finds that neighborhood-scaled housing voucher limits would be "both more effective at moving households to neighborhoods with lower poverty rates, and less expensive to implement, than a policy that increases the maximum voucher amount by 20 percent" (Geyer, 2017: 58).

Data and Local Pushback Against the SAFMR

When HUD proposed the SAFMR, numerous local PHAs and advocacy organizations opposed the proposal, often citing data concerns in their criticisms.

A coalition of the PHAs in Oakland, one of my case study areas, commented that the existing evidence on the SAFMRs is limited to one HUD metropolitan FMR area, Dallas, TX, where vacancy rates are significantly higher when compared with rates in California (Johnson, 2016b). The letter argues that the SAFMRs would limit the purchasing power of vouchers in less expensive neighborhoods and thus reduce the overall number of units listed below FMRs. In a separate comment submitted to HUD, the Oakland Housing Authority also argued that the inadequacies of the ACS would worsen the situation for voucher recipients in rapidly gentrifying neighborhoods (Johnson, 2016a). A coalition of East Bay Housing Organizations, also in Oakland, emphasized their concerns about the lagging nature of the ACS preventing FMRs from keeping pace with the market (Levin, 2016). Lastly, the Santa Clara County Housing Authority also questioned the accuracy and relevance of ZIP Code-scaled FMRs. They argued it would harm voucher recipients who found housing in some high-income census tracts that are sandwiched inside lower rent ZIP Codes (Harsasz, 2016).

HUD responded to these and other concerns by allowing the SAFMRs to apply only in areas that met two conditions.

1. The metropolitan FMR area has a vacancy rate above 4 percent.
2. The metropolitan FMR area has at least 20 percent of its below-FMR stock in ZIP Codes with SAFMRs above 110 percent of their respective metropolitan FMRs.[4]

[4] Final rule.

These stipulations might ensure a sufficient supply of below-FMR stock in these high-end ZIP Codes can offset the loss of below-FMR units in less expensive ZIP Codes. These changes address concerns related to overall vacancies and availability issues. They do not eliminate the possibility that lower vacancies in expensive ZIP Codes might mean the SAFMRs will reduce the total number of below-FMRs vacancies across areas. They also do not address the underlying issue of HUD's reliance on time-lagged ACS data and its potential impacts to voucher users in gentrifying communities. These criticisms and HUD's response inform the hypotheses presented in the following section. No prior empirical work with rental listings data explores these challenges with FMR formulation and their implications for enabling voucher recipients to penetrate the market.

Hypotheses

The primary purpose of this article is to test the potential for the SAFMRs to increase the number of units below FMRs in high-opportunity areas. The article utilizes a proprietary dataset of for-rent listings derived from online sources that do not face the drawbacks of the ACS at small geographies. To that end, the first hypothesis is—

1. The SAFMRs will increase the percentage of listings that are below FMR in high-opportunity areas.

Critics of the SAFMRs suggest the policy will not increase the number of below- FMR units in markets with tight vacancy rates. They argue it could reduce the overall share of units below FMR. Critics also note the SAFMRs may exacerbate the impacts of gentrification on voucher recipients due to the time lag between data collection and policy implementation. To assist in clarifying the ways these issues interact with the SAFMRs, I test three additional hypotheses.

2. A switch to the SAFMRs will reduce the overall share of listings below FMR in each HUD metropolitan FMR area.

3. At the ZIP Code level, vacancy rates will correlate positively and significantly with SAFMR-induced increases in listings below FMR.

4. Areas that lose below- FMR listings under the SAFMRs are also those experiencing the most rapid loss in below-FMR units under the existing FMR system (presumably, from gentrification).

The fourth hypothesis tests the idea that areas that saw below-FMR units vanishing due to gentrification were also those which would see a reduction of below-FMR listings under the SAFMRs, as suggested by several comments to HUD (Johnson, 2016a; Levin, 2016).

I selected proprietary rental listings data for this study in light of the many pitfalls of relying on ACS data noted in the literature review. Concerns do exist about the value of rental listings for policy analysis, however. The only study utilizing listings to measure FMRs in the market found strikingly different results than ACS-based estimates in the areas studied in this article (Boeing and Waddell, 2016). To further our understanding of this emerging source of data, I compare my data's findings in these areas with both Boeing and Waddell's and the ACS to test a final hypothesis.

5. Proprietary rental listings data will more closely reflect Boeing and Waddell's (2016) Craigslist findings on the share of units below FMR than findings derived from the ACS.

Data and Methods

I use a rental database prepared by Rent Jungle. The database contains information on rental listings gathered from internet sources such as Craigslist, as well as the web-listings provided by newspapers, other proprietary gatherers, property management companies, and community web pages. Rent Jungle uses a web-based tool to extract the data from each of these sources once a week on an automated basis and compiles them into a database on a central server. The dataset thus provides a weekly snapshot of all rental listings posted online or in print in each market. This snapshot also provides the location, number of bedrooms, and number of bathrooms for each of these listings. In total, this comprehensive for-rent database has more than 150,000 listings across the five HUD metropolitan FMR areas for 2012 and 2013.

Limitations

The potential statistical power of such a large sample does not make this dataset immune from criticism. This dataset faces several limitations. First, it measures contract rent, although HUD sets FMRs using gross rent, which includes utilities. The Rent Jungle data do not specify which listings include utilities and which do not. Second, the data do not capture the vacancy rate of listings in multifamily buildings. This missing information means the dataset may underestimate rental availability on very large multifamily properties. For example, the data might show a large apartment complex listing a single, two-bedroom unit every week from June through October. This listing will appear in the dataset as one consistently listed two-bedroom unit. In reality, however, the building may have three or four different two-bedroom units becoming available throughout that time. Reflected in the data, however, is only that one consistent listing at the same address with the same number of bedrooms during that time span. This example illustrates the third and final drawback, which is that the dataset does not uniquely identify each available unit. Because of this disadvantage, this study can only comment on the general impacts of the SAFMRs across each area studied but not the precise magnitudes of such impacts.

These limitations also illustrate why these data, although still helpful for academic research and this particular study, may be inappropriate for use by HUD in setting FMRs. Beyond these technical limitations, proprietary data may not fit the criteria set by GAO (2005) that the FMR documentation system be transparent, reproducible, and consistent across geographies.

Identifying Unique Listings

Boeing and Waddell (2016) take advantage of Craigslist's use of a unique identifier to pinpoint and track individual listings, thereby removing duplications of the same listing in their dataset. My proprietary listings do not offer such an easy solution. However, my interest in the rental market is relatively straightforward—I need the inventory of available rentals from which aspiring voucher tenants could choose in a given year. Toward this goal, I set up a series of heuristics to identify unique listings. First, I assigned a unique observation identification number for every listing with a unique combination of the following—an address, number of bedrooms, and year of listing (2012 versus 2013). If the data listed one of these unique observations twice within a minimum 6-month time span, I split it into two unique listings, 6 months apart, to account for the extended availability and the possibility of multiple listings therein. In those cases in which a unit was listed in both 2012 and 2013, with its availability consistent but shifting from 2012 into 2013, I allowed for the unit to count once in each year if the total span of its availability was greater than 6 months (for example, if it was available from September 2012 through April 2013). These heuristics reduced the total sample from 150,000 to 95,868 units. The final culled listings dataset provides an average of 240 observations per ZIP Code, still far higher than the number of new renters most likely provided by the ACS, roughly an average of 44 observations per census tract.[5]

Addressing hypotheses four and five requires contextualizing the 2012–2013 analysis within broader trends of rental market change. To identify these trends, I drew on the same Rent Jungle database to procure listings from 2011 through 2015 and applied the same heuristics to these data to ensure consistency.

The dataset covers five HUD metropolitan FMR areas in California—Oakland, Sacramento, San Diego, San Francisco, and San Jose—which are all consistently ranked among the most expensive rental markets in the United States (NLIHC, 2016b).

Applying FMRs and SAFMRs

I classified each rental listing as above or below established FMRs based on tables provided on HUD's website (HUD, 2017a). I then repeated the same step using the hypothetical SAFMRs HUD also posts online. I revised the hypothetical SAFMRs to be no less than 90 percent of the previous year's FMR, per HUD's implementation of the rule.[6] This step required estimating the revised SAFMRs for 2012 to produce the final SAFMRs for the observations in 2013. Thus, the results of this study present an average impact of the SAFMRs during 2 years of consecutive implementation.

Defining High Opportunity

HUD's final rule issuing the SAFMRs refers specifically to increasing voucher holder presence in high-opportunity neighborhoods. HUD characterizes high-opportunity neighborhoods as those with low-poverty rates and access to good schools.[7] I define opportunity in terms of neighborhood poverty rate, drawing on tract poverty rates from the 2010–2014 ACS. I define school quality using an average of the California Academic Performance Index (API) score of the three elementary schools nearest to each tract. I select this source as a previous study on the ability of voucher recipients to access high-performing schools also draws on the API (Basolo, 2014).

[5] Although the ACS does not publish sample sizes for small scales, using state-level sample sizes, we can deduce that the 2014–2010 ACS contains roughly 390 responses per ZIP Code in California to represent the total housing stock (U.S. Census Bureau, 2016b). Because roughly one-half of California households rent, the ACS thus probably averages 195 rental units surveyed per ZIP Code. As roughly 12 percent of renters move annually (U.S. Census Bureau, 2015), then we can estimate the ACS contains around 24 new movers per ZIP Code in California compared with our sample of nearly 240 listings per ZIP Code.

[6] Final rule.

[7] Final rule.

Results

This section presents results by hypothesis, starting with the first—that the SAFMRs will increase the percentage of listings that are below FMRs in high-opportunity areas. Exhibit 1 presents the results with respect to tract-level poverty rates.

In tracts with poverty rates of less than 10 percent, the SAFMRs increase the percent of listings below FMR in every HUD metropolitan FMR area except San Francisco, where they decline slightly. Increases are the most dramatic in Sacramento, with a 34-percentage-point increase in below-FMR listings, and San Diego, with a 28.1-percentage-point increase in these low-poverty tracts. In tracts with poverty rates of more than 40 percent, in contrast, a sharp drop in below-FMR units occurs in the Oakland market of 18 percentage points. In the other four areas, however, the below-FMR share in high-poverty tracts declines between 0 and 11 percentage points. With the exception of San Francisco, these results suggest the SAFMRs will improve the number of listings below FMR in low-poverty neighborhoods. Exhibit 2 presents the results for the average API score of nearby schools.

In tracts near schools with the highest API scores, the percent of listings below FMR increases in every jurisdiction. These increases range from 1 percentage point in San Francisco to 38 percentage points in San Diego. In tracts near schools with the lowest API scores, the percent of listings below FMR decline modestly, from 0.6 percentage points in San Diego to 11 percentage points in San Jose.

Exhibit 1

Percent of Listings Below FMR by Area, Tract Poverty Rate, and FMR System

HUD Metropolitan FMR Area	Tract Poverty Rate (%)	Current FMR (%)	SAFMR (%)	Change (%)
Oakland-Fremont, CA	0–10	23.2	43.1	19.9
	10–20	37.3	49.5	12.2
	20–30	72.5	71.4	– 1.1
	30–40	77.6	68.0	– 9.6
	40 or more	64.2	45.3	– 18.9
Sacramento--Roseville--Arden-Arcade, CA	0–10	40.1	74.3	34.2
	10–20	73.4	82.5	9.1
	20–30	90.3	83.5	– 6.9
	30–40	93.1	86.0	– 7.0
	40 or more	89.0	82.1	– 6.9
San Diego-Carlsbad, CA	0–10	31.0	59.1	28.1
	10–20	56.6	64.8	8.2
	20–30	79.2	71.9	– 7.3
	30–40	68.5	74.2	5.7
	40 or more	82.7	71.6	– 11.2
San Francisco, CA	0–10	16.5	13.8	– 2.7
	10–20	17.7	10.6	– 7.2
	20–30	16.7	6.2	– 10.6
	30–40	16.2	10.0	– 6.2
	40 or more	38.8	35.9	– 2.9
San Jose-Sunnyvale-Santa Clara, CA	0–10	19.8	29.5	9.7
	10–20	40.8	34.8	– 6.0
	20–30	59.1	40.9	– 18.2
	30–40	68.3	46.2	– 22.1
	40 or more	75.0	75.0	0.0

FMR = Fair Market Rent. HUD = U.S. Department of Housing and Urban Development. SAFMR = Small Area Fair Market Rent.

Exhibit 2

Percent of Listings Below FMR by Area, School API Score, and FMR System

HUD Metropolitan FMR Area	School API Scores	Current FMR (%)	SAFMR (%)	Change (%)
Oakland-Fremont, CA	Less than 770	68.7	65.6	– 3.0
	770–820	50.4	60.9	10.5
	820–870	36.2	47.7	11.4
	870–915	14.6	36.9	22.4
	915 or more	12.5	40.8	28.3
Sacramento--Roseville--Arden-Arcade, CA	Less than 770	87.6	79.4	– 8.2
	770–820	74.9	80.8	5.9
	820–870	68.2	83.7	15.5
	870–915	37.9	77.1	39.2
	915 or more	28.6	61.1	32.5
San Diego-Carlsbad, CA	Less than 770	71.3	70.8	– 0.6
	770–820	74.8	71.5	– 3.3
	820–870	62.0	67.1	5.1
	870–915	40.9	61.7	20.8
	915 or more	16.4	54.7	38.3
San Francisco, CA	Less than 770	15.0	9.2	– 5.8
	770–820	17.8	8.3	– 9.4
	820–870	16.6	11.8	– 4.8
	870–915	18.6	17.4	– 1.3
	915 or more	13.8	14.8	1.0
San Jose-Sunnyvale-Santa Clara, CA	Less than 770	38.4	27.2	– 11.2
	770–820	47.0	42.3	– 4.7
	820–870	22.0	28.2	6.2
	870–915	33.4	47.2	13.8
	915 or more	14.5	22.5	8.0

API = Academic Performance Index. FMR = Fair Market Rent. HUD = U.S. Department of Housing and Urban Development. SAFMR = Small Area Fair Market Rent.

The overall rate of declines in exhibit 2 are lower than in exhibit 1, as many neighborhoods with significant losses of below-FMR listings under SAFMRs were near schools that did not contain API scores in the dataset at the time of this analysis, a surprising finding. Taken together, however, the results on poverty rates and school quality demonstrate the SAFMRs will increase the percentage of listings that are below FMRs in high-opportunity areas, as expected, with the notable exception of San Francisco.

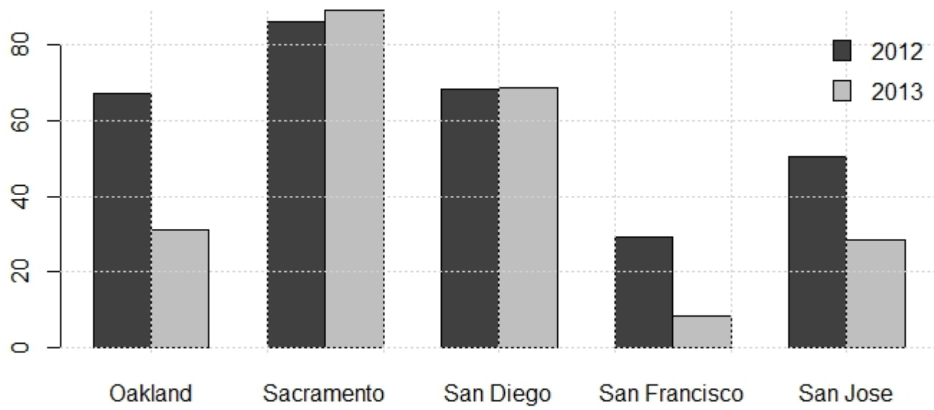
Expanding on Hypothesis One: Why Is San Francisco Different?

The SAFMRs fail to raise the share of below-FMR units in San Francisco in this time period, because the SAFMRs did not fully match stratospheric rents in that area's expensive ZIP Codes. To assess this failure properly, I limited the dataset to units in ZIP Codes with SAFMRs at 110 percent or above traditional FMRs. I then measured the percentage of listings in these high SAFMR ZIP Codes that were below their related SAFMRs and plotted the difference across HUD metropolitan FMR areas, shown in exhibit 3. Thus, the percentages in exhibit 3 represent the percent of listings a voucher recipient could afford under the SAFMRs in only the high-SAFMR ZIP Codes.

In San Francisco, 25 percent of listings in expensive ZIP Codes would have fallen below FMRs under the hypothetical SAFMRs in 2012. This decrease means that the SAFMRs would have enabled voucher holders to afford only 25 percent of listings in the ZIP Codes in which maximum

Exhibit 3

Percent of Listings in High-SAFMR ZIP Codes Below the SAFMRs, 2012 and 2013



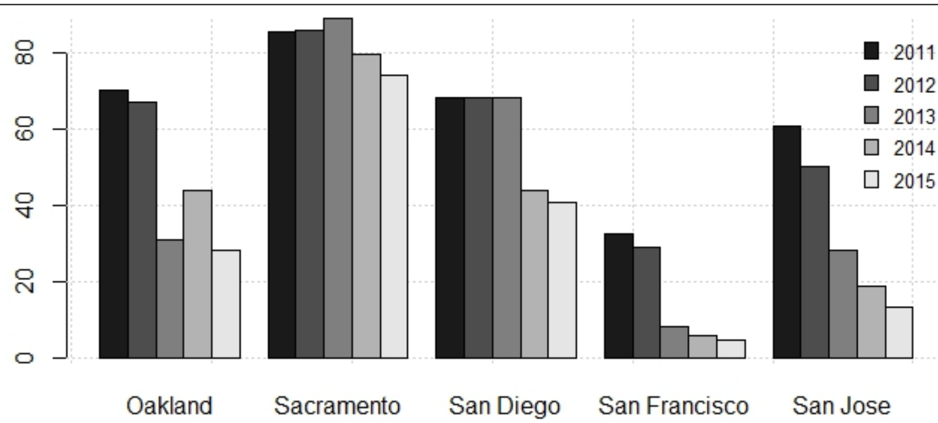
SAFMR = Small Area Fair Market Rent.

rents would have risen under SAFMR policy. Most listings in expensive ZIP Codes in Sacramento and San Diego, in contrast, would have fallen below FMRs under the same scenario, suggesting the SAFMRs would have significantly increased the number of listings affordable to voucher holders in expensive ZIP Codes in those cities. In all three Bay Area markets, a temporal pattern appears to emerge. These percentages would have declined by roughly one-half across the Bay Area from 2012 to 2013 under the SAFMRs, implying the SAFMRs would not have kept pace with rising rents in these ZIP Codes.

As the dataset acquired for this project spans 5 years, I use the same 5-year timeframe to plot the ways in which the statistics presented in exhibit 3 change across all five HUD metropolitan FMR areas during 5 years. Exhibit 4 shows the changes. During this period, the SAFMR system would

Exhibit 4

Percent of Listings in High-SAFMR ZIP Codes Below the SAFMRs, 2011–2015



SAFMR = Small Area Fair Market Rent.

not have kept pace with observed rents in the San Francisco Bay Area. Exhibit 4 illustrates the concerns of the East Bay PHAs that FMRs do not rise at the same pace as rents increases in that area (Johnson, 2016b). These findings could result from HUD's decision to limit SAFMRs to no more than 150 percent of traditional FMRs. I replicated this analysis under hypothetical SAFMRs that could rise above the 150 percent cap and found very similar results. Only 3 percent of listings in more expensive ZIP Codes saw their SAFMRs increase with the 150 percent cap removed.

The data suggest that the Bay Area is experiencing rapid rent increases that are particularly punitive to voucher recipients, regardless of the FMR system adopted. The failure of these higher-end SAFMRs to make a difference may explain the results for hypothesis two, discussed in the next subsection.

Hypothesis Two: SAFMRs Will Reduce the Overall Share of Listings Below FMR

Only in San Francisco do the SAFMRs reduce the overall share of listings below FMR, from 16.5 to 11.9 percent. In the other four areas, the share of listings below FMR increases, as shown in exhibit 5. In Oakland, Sacramento, and San Diego, a sufficient number of listings become below FMR in high-cost ZIP Codes to cancel out the loss of below-FMR units in less expensive ZIP Codes. In San Jose, the SAFMRs break even against the existing FMRs.

The increases range from only 2 percentage points in San Jose to nearly 15 percentage points in Oakland. These results suggest the SAFMRs as implemented in the HUD rule will not cause a cataclysmic loss of below-FMR units in its first 2 years of implementation. Given that HUD's ruling allows for annual stepwise reductions in SAFMRs in low-rent areas, however, these results do not offer insights on the long-term impact of the SAFMRs on the overall availability of below-FMR units.

A major potential drawback of the analysis thus far is the potential for real vacancy rates to bias the picture painted in this dataset. I address this problem in the next subsection.

Exhibit 5

Share of Listings Below FMR by Area and FMR System, 2012–2013

HUD Metropolitan FMR Area	Current FMR (%)	SAFMR (%)	Change (%)
Oakland-Fremont, CA	34.9	49.7	14.8
Sacramento--Roseville--Arden-Arcade, CA	69.6	80.6	10.9
San Diego-Carlsbad, CA	52.9	64.7	11.8
San Francisco, CA	16.5	11.9	– 4.6
San Jose-Sunnyvale-Santa Clara, CA	30.6	32.6	2.0

FMR = Fair Market Rent. HUD = U.S. Department of Housing and Urban Development. SAFMR = Small Area Fair Market Rent.

Hypothesis Three: Vacancy Rates Will Correlate Positively With the SAFMR's Effect

To test this hypothesis, I limited my analysis to only those ZIP Codes with rental vacancy rates significantly different from zero in the ACS, which reduced the data 50 percent. I also limited the analysis to ZIP Codes with more than 40 rental listings in my dataset, which did not further alter the sample size. With or without these adjustments, however, my results are the same. No apparent relationship exists between SAFMR shift and ZIP Code vacancy rates. I plot the relationship of these two variables across the 243 ZIP Codes with sufficient data in exhibit 6.

Exhibit 6

ZIP Code Vacancy Rates Plotted Against the Percent Change in Below-FMR Listings From the SAFMR

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

Although regression analyses failed to specify a significant relationship, visual inspection of exhibit 6 offers some insights. All the ZIP Codes that had a 60–percentage-point increase or greater in below-FMR listings under the SAFMRs reported vacancy rates of less than 5 percent. ZIP Codes with vacancy rates of greater than 10 percent either saw a modest decline in below-FMR units under the SAFMRs or were unaffected.

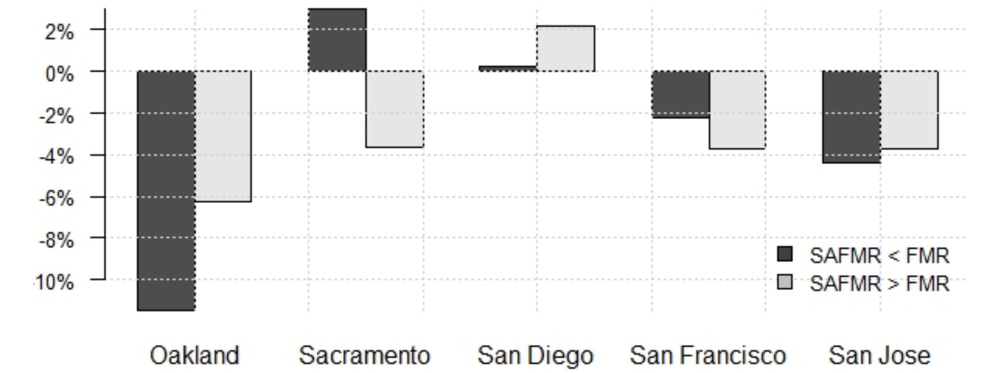
If a significant relationship exists between vacancy rates and the impact of the SAFMRs at these smaller geographies, the SAFMRs could severely restrict the number of units voucher recipients could afford. Fortunately, nothing in this study suggests this result is a major possibility, although vacancies from rigorous market studies could paint a different picture than the flawed ACS estimates used here. Regardless, HUD's decision to limit implementation of the SAFMRs to areas with vacancy rates above 4 percent offers some assurance that vacancy rates may not be a major challenge for voucher recipients in areas using the SAFMRs.

Hypothesis Four: Areas That Will Lose Below-FMR Listings Under the SAFMRs Are Those Experiencing the Most Rapid Loss in Below-FMR Units

To test this hypothesis, I categorized all units into two geographic groups—those in ZIP Codes in which the SAFMRs were above the FMR, thus prospectively increasing voucher holders' rental opportunities in that ZIP Code, and those in ZIP Codes in which the SAFMRs dropped below the FMR, and voucher holders would have fewer options. I then measured the actual loss of below-FMR listings under the existing statutory FMRs over time and bifurcated these results into these two geographic groups, producing exhibit 7.

Exhibit 7

Percentage-Point Shift in Share of Below-FMR Listings, 2011–2015, Under Existing FMRs, by Impact of SAFMRs



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

Exhibit 7 shows that in Oakland, those ZIP Codes that would lose below-FMR listings under the SAFMRs were already experiencing an 11-percentage-point drop in below-FMR listings under existing policy. In contrast, ZIP Codes that would see uplift in below-FMR units under the SAFMRs witnessed only a 6-percentage-point drop in below-FMR listings. These results only reconfirm the concerns of activists and PHAs in Oakland (Johnson, 2016a, 2016b; Levin, 2016). Exhibit 7 suggests this dynamic of the SAFMRs aggravating existing market trends would not have occurred in San Diego, San Francisco, and San Jose.

The other remarkable finding presented in exhibit 7 concerns Sacramento. Between 2011 and 2015, the ZIP Codes in Sacramento in which SAFMRs would have increased below-FMR listings are also those that witnessed drops in the number of below-FMR listings under existing policy. This outcome suggests Sacramento will benefit from the SAFMRs if this trend continues past 2015.

Hypothesis Five: Proprietary Rental Listings Data Will More Closely Reflect Boeing and Waddell's (2016) Estimation of the Share of Units Below FMR Than the ACS

As Boeing and Waddell utilized data in 2014, I use 2014 listings from my database to compare measurements of the share of units below FMR in exhibit 8. I disaggregate the results by number of bedrooms and the MSA designations that Boeing and Waddell used, which are different from the HUD metropolitan FMR area designations used elsewhere in this article.

In line with my hypothesis, Rent Jungle and Craigslist are more closely aligned to each other than the ACS in 8 of the 12 statistics examined here (66 percent). In all eight of these cases, these two datasets show fewer listings below FMR than the ACS. In 6 of the 12 comparisons, the Rent Jungle and Craigslist results are less than 5 percentage points apart.

Discrepancies between the two rental listings sources may be the results of my heuristics for identifying unique listings and my approach may need refinement. Alternatively, Rent Jungle's

Exhibit 8

Percent of Units Below FMR According to Craigslist, Rent Jungle, and the ACS

MSA	Bedrooms	Craigslist (%)	Rent Jungle (%)	2014 PUMS 1-Year Recent Movers (%)
Sacramento--Roseville--Arden-Arcade, CA	1	58	67	70
San Diego-Carlsbad, CA	1	17	28	51
San Francisco-Oakland-Hayward, CA	1	18	16	41
Sacramento--Roseville--Arden-Arcade, CA	2	62	63	73
San Diego-Carlsbad, CA	2	24	27	36
San Francisco-Oakland-Hayward, CA	2	26	20	27
Sacramento--Roseville--Arden-Arcade, CA	3	69	73	62
San Diego-Carlsbad, CA	3	39	34	55
San Francisco-Oakland-Hayward, CA	3	37	30	62
Sacramento--Roseville--Arden-Arcade, CA	4	53	66	71
San Diego-Carlsbad, CA	4	36	36	51
San Francisco-Oakland-Hayward, CA	4	47	57	61

ACS = American Community Survey. FMR = Fair Market Rent. MSA = metropolitan statistical area. PUMS = Public Use Microdata Sample.
Sources: Craigslist data from Boeing and Waddell (2016); Rent Jungle data from author's calculation

proprietary listings might also include some higher-end rentals that property managers do not post to Craigslist, presenting a market that appears more expensive than the market viewed via Craigslist. The variation in findings among the two similarly organized listing sources demonstrates their limitations as suitable replacements to the ACS for FMR documentation. Proprietary providers may not be willing to make their assumptions, methods, and techniques publicly available, as HUD is required to do.

Conclusions

Switching to the SAFMRs increases the share of rental listings below FMR in low-poverty neighborhoods in the Oakland, Sacramento, San Diego, and San Jose HUD metropolitan FMR areas. It does the opposite in San Francisco. Across all five areas, shifting to the SAFMRs increases the share of rental listings below FMR in neighborhoods with high performing schools, although data limitations prevent conclusions about below-FMR shifts in less expensive areas. This article reveals that in San Francisco, the hypothetical SAFMRs in high-rent areas are simply not high enough to increase the below-FMR rate in these neighborhoods. Although it might seem appropriate to recommend even higher FMRs for these neighborhoods, the cost of providing vouchers in the most expensive parts of the nation's most expensive metropolitan areas may not be worth the trade-off of reducing the number of families the program could serve, as some critics of the SAFMRs point out

(NAHB, 2017). Regardless, this article finds the SAFMRs may increase voucher holders' options in high-opportunity neighborhoods, even in some of the most expensive metropolitan areas in the United States. This benefit does not guarantee voucher recipients will be able to use vouchers in these areas, however, as the SAFMRs do not address source of income discrimination.

I also explored several concerns expressed by local activists and PHAs in response to HUD's SAFMR ruling. San Francisco would see an overall drop in below-FMR listings, although the other four areas would see overall increases. However, given the trends tracked in exhibit 4, Oakland and San Jose might see a net drop in below-FMR listings if they adopted the SAFMRs at present.

The results also illustrate the way areas that would lose below-FMR listings under the SAFMRs experienced a faster drop in below-FMR rates under existing policy in Oakland. This outcome implies the SAFMRs might only worsen the challenges of voucher recipients in that area. These results are broadly consistent with concerns expressed by advocates and agencies in Oakland, who are concerned with unprecedented upward swings in the local rental market.

In contrast to Oakland, Sacramento may likely benefit from the SAFMR. This study finds that the SAFMRs may work most effectively in Sacramento and San Diego. That HUD only initially implemented the SAFMRs in these two markets among the five studied here inspires confidence in HUD's criteria for applying the SAFMRs to metropolitan areas.

This study also compared estimates of the share of units below FMRs across three sources of data, finding the ACS varied significantly from real-time listings data. Unfortunately, proprietary listings data do not meet the criteria established by GAO (2005) that the FMR system be entirely consistent, transparent, and replicable. Changes to the FMR system's use of the Consumer Price Index and trend-adjustment factors may be the most effective way to alleviate the challenges faced by voucher recipients in tight markets while maintaining methodological transparency.

Lastly, this study demonstrates the importance of scale when implementing housing policies and programs. Rents and land values are highly autocorrelated across space. The finer the scale at which market-oriented policy thresholds are determined, the more even policy outcomes are likely to be. This principle should be explored further, as it may have implications for other aspects of urban housing policy, from supply-side subsidy allocations to rent control.

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Author

Matthew Palm is a research fellow at the University of Melbourne.

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Can a Car-Centric City Become Transit Oriented? Evidence From Los Angeles

Jenny Schuetz
Brookings Institution

Genevieve Giuliano
University of Southern California

Eun Jin Shin
Yale-NUS College

Abstract

The urban built environment develops over decades around fixed infrastructure. Los Angeles began its major growth at the dawn of the automobile era and became a low-density, dispersed metropolis organized around a vast freeway system. Since the 1990s, local governments have sought to restructure Los Angeles, shifting toward higher density, mixed-use housing and commercial development. A large investment in new rail transit lines is seen as critical to achieving these land use goals, mainly through promotion of transit-oriented development. In this article, we examine how employment patterns have changed around newly built Los Angeles rail stations. Results suggest that employment did not increase near stations immediately before or after station opening, but a few stations saw increased employment 5 to 10 years after opening.

Introduction

For most of the 20th century, Los Angeles was the quintessential car-oriented city. Over the past 20 years, however, local and regional governments have invested significant resources in building rail transit infrastructure that connects major employment centers, including downtown Los Angeles, Long Beach, Pasadena, and the eastern Wilshire Corridor. One goal of transit infrastructure is to catalyze high-density, mixed-use housing and commercial development within walking distance of rail stations, known as transit-oriented development (TOD). By increasing the accessibility of station areas, the building of new stations should increase surrounding land values, leading to higher-density development. In this article, we examine changes in employment patterns around Los Angeles County Metropolitan Transit Authority (LA Metro) rail stations from 1990 to 2010. The analysis examines whether station areas have experienced changes in the density or composition of employment following station opening, and explores the time frame in which such changes may happen.

Standard urban economics models yield several hypotheses for how and why economic activity might change in areas where new rail stations are built. Following the standard monocentric city model, land values are highest at the central business district (CBD) and decline moving outward in proportion with increasing travel costs (Alonso, 1964; Brueckner, 1987; Mills, 1967; Muth, 1969). Building a rail station that connects the station's neighborhood with the CBD or employment subcenters should increase the accessibility of that neighborhood, thereby increasing land values and encouraging higher density development nearby (Anas, 1995; Glaeser and Kohlhase, 2004). Neighborhoods around rail stations should be relatively more attractive both to firms and households. Firms can attract more workers due to increased accessibility, as well as more consumers to convenient locations, particularly in household-serving industries such as retail, food service, and healthcare. Households will be willing to pay higher housing prices in exchange for lower transit costs.

How much land values and economic activity increase near stations depends on the extent of improved accessibility to the location; for instance, stations that link to larger and denser rail networks should have greater impacts on land values. Rail lines that simply replace existing bus transit service have little impact on accessibility. Because most passengers access rail stations by walking, station effects will be highly localized. Prior research has also posited some potential negative impacts of rail stations on nearby areas. Rail stations may increase noise, traffic congestion, or crime in the adjacent area; these nuisances are likely stronger disamenities for households than for commercial uses. Land values around stations may fluctuate in the short run, both prior to and immediately after opening, before reaching long-run equilibrium. The relationship between short-run and long-run land values is somewhat ambiguous. For instance, anticipation of increased demand may cause short-run spikes in land values, beyond prices that developers are willing to pay, which can deter or delay development. This is particularly likely if small parcel owners become "holdouts" (Brooks and Lutz, 2016). Conversely, developers may perceive untested locations as excessively risky and delay undertaking projects until some first-mover demonstrates actual profits (essentially underestimating long-run land values in the short run).

A broad empirical literature has attempted to identify the impacts of rail transit investments on outcomes such as transit ridership, land values, housing prices, population and housing density, employment composition, population characteristics, and crime (Baum-Snow and Kahn, 2005; Billings, 2011; Billings, Leland, and Swindell, 2011; Boarnet and Crane, 1997; Bollinger and Ihlanfeldt, 1997; Bowes and Ihlanfeldt, 2001; Cervero and Landis, 1997; Debrezion, Pels, and Rietveld, 2007; Dubé, Thériault, and Des Rosiers, 2013; Giuliano and Agarwal, 2010; Handy, Cao, and Mokhtarian, 2005; Kahn, 2007; Lin, 2002; Mathur and Ferrell, 2013; McMillen and McDonald, 2004; Poister, 1996; Renne and Ewing, 2013; Winston and Maheshri, 2007). As well as measuring different outcomes, these studies cover different cities, time periods, and transit types (heavy rail, light rail, and streetcar). Results from these studies are somewhat mixed, although one relatively consistent finding is that the extent of changes in property values, employment, and related economic outcomes depends on the level of transit ridership; low ridership on average produces smaller impacts.

Only a few prior studies have examined the LA Metro system, which is new relative to "legacy" systems such as those in New York City, Boston, and Chicago, or even second-wave subways such as the Bay Area Rapid Transit (BART) in the San Francisco Bay Area and Washington, D.C.'s Metro. Kolko (2011) and Schuetz (2015) examined employment near newly opened rail stations in Los Angeles and several other large California metropolitan areas; both find little change in employment levels near stations. Redfearn (2009) found no average change in housing prices near Los Angeles rail stations but furthermore found that the average conceals substantial variation in housing price changes across stations. Similarly, in a qualitative study of physical redevelopment near five LA Metro stations, Schuetz, Giuliano, and Shin (2017) found that TOD is emerging unevenly across station neighborhoods. Areas that experienced changes in land use or buildings have strong localized real estate markets, have zoning that allows high-density residential and commercial development, and benefited from highly targeted local government engagement. Weak property values and incompatible zoning both contribute to lack of redevelopment near some stations.

This article makes several contributions to the existing literature. First, relatively few studies have examined the impacts of rail transit on employment or commercial activity, although retail, services, and related activities are key components of TOD. Second, we are able to conduct longitudinal analysis of treatment and control areas over a 20-year period, which allows us to test for prestation anticipation effects and lagged changes. Third, impacts of transit in Los Angeles have been less studied than in many other cities. Los Angeles' history as a car-centered city makes this a particularly interesting empirical setting to determine whether introduction of a rail system has the capacity to change land use patterns. This research is particularly relevant in light of ongoing rail and streetcar investment in many U.S. cities, including Charlotte, Cincinnati, Denver, and Washington, D.C.

In this analysis, we combine data on the location and opening dates of 28 rail stations in Los Angeles County with establishment-level employment data. We measure the level and industrial composition of employment within 0.25- and 0.5-mile catchment areas of newly opened rail stations, before and after opening. As a comparison group, we identify a set of major road intersections in the same neighborhoods as stations but outside direct catchment areas. We use a difference-in-differences approach to compare changes in employment outcomes before and after opening for station and control areas. Results indicate that the areas selected for new stations had unusually high employment density prior to station opening. No evidence suggests that employment near stations changed within 5 years before or after station opening, but some results suggest that a few stations experienced increased employment within a 5- to 10-year period after opening. One possible explanation for the long lag is that most stations were built in already densely developed areas, where redevelopment is costly and slow. Alternatively, proximity to stations may become more valuable as the network size expands through additional lines.

Our results offer two key insights to transit planners who are building or expanding rail networks in other metropolitan areas, particularly car-oriented cities with multiple employment centers and a dense urban fabric. First, transit infrastructure is more likely to deliver long-run benefits than short-run stimulus. Second, planners should be clear about the primary goal of building rail systems—weighing access to existing jobs versus stimulating new residential development—when choosing station locations and coordinating housing or land use policies.

The remainder of this article is organized as follows. Section 2 provides more context on Los Angeles' rail network. Section 3 discusses the data sources and empirical methods. Results of the analysis are presented in Section 4. Section 5 discusses policy implications and concludes.

Background on Los Angeles Rail Network

Even after roughly $9 billion (nominal) of public investment in rail infrastructure, Los Angeles remains a car-oriented city (Nelson and Weikel, 2016). As of the late 2000s, 84 percent of the city's residents commuted to work by car, with fewer than 7 percent using mass transit (exhibit 1). Even among transit riders, over 90 percent of commuters relied on buses rather than rail; these market shares have not changed appreciably since rail service began in 1990. The relatively low ridership raises questions about whether proximity to rail stations is highly valued by residents, workers, and firms, and thus whether station access will be capitalized into higher land values and increased employment. The utility of a rail network is determined by how much it increases accessibility, that is, to what extent it facilitates passengers' ability to reach desirable locations. LA Metro stations are relatively thinly spread across a large geographic area (exhibits 2 and 3); on average, each station is 1.25 miles from its nearest station (Schuetz, 2015). The existing rail lines link several large employment centers to one another, but many residential areas, and a large share of the population, are too far from any rail station to make using the system practical for daily commuting even when considering using bus service to transfer to the nearest rail station.

One means of illustrating the demand for rail stations is the number of daily boardings (exhibit 4). Across all study-area stations, daily boardings averaged about 6,700 in 2013, the most recent year for which data are available. Boardings vary widely across stations and lines; the Purple and Red Line stations in downtown and central Los Angeles draw the most riders, with over 13,500 average boardings per day, compared to about 1,700 boardings at the Gold Line stations in Pasadena and the Arroyo Seco corridor north of downtown. Connectivity to the broader network is correlated

Exhibit 1

Mode Share for Daily Journey to Work, Selected U.S. Counties (2006–2010)

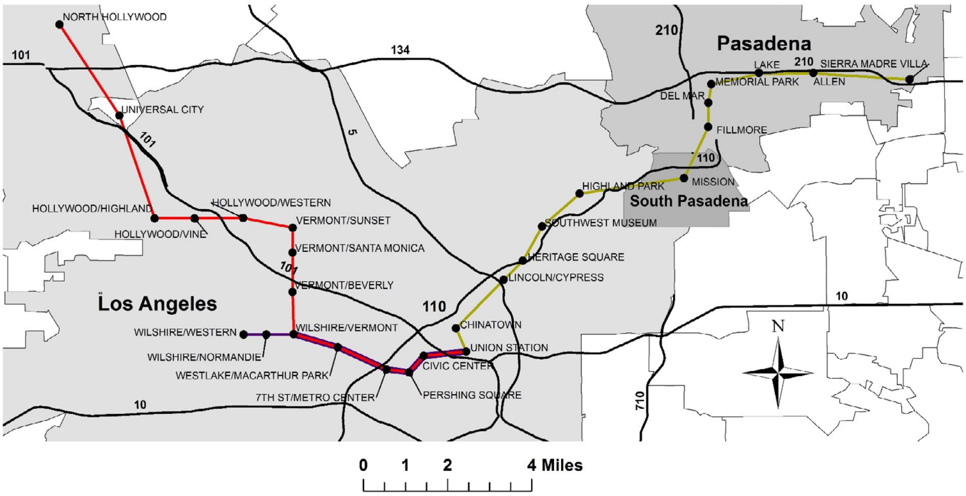
County	Rail	Bus	Car	Bike or Walk	Other
New York City, New York	39.1	12.2	30.0	10.6	8.1
Suffolk, Massachusetts	17.4	11.6	51.0	14.5	5.6
San Francisco, California	9.7	20.7	47.4	12.4	9.8
Cook, Illinois	6.2	7.4	73.1	4.8	8.6
Los Angeles, California	0.4	5.7	84.3	3.5	6.1
Dallas, Texas	0.4	2.2	90.6	1.5	5.3
King, Washington	0.1	9.9	77.7	5.2	7.2

Notes: Rail includes subway, elevated, streetcar, and trolley car. Car includes truck and van. New York City includes five constituent counties (Bronx, Kings, New York, Queens, and Richmond).

Source: Calculations based on Ruggles et al. (2015), 2006–2010 Integrated Public Use Microdata Series sample of American Community Survey

Exhibit 2

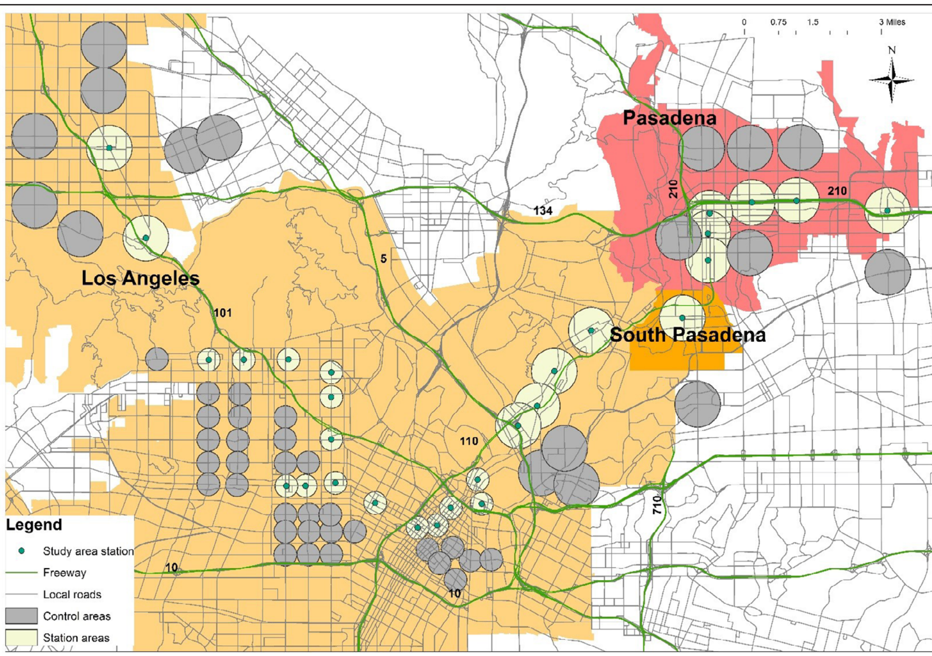
Study Area Metro Stations



Note: Map shows only Metro stations included in study (excludes Gold Line stations that opened after 2009 and all Blue Line stations).
Source: Data assembled from Los Angeles County Metropolitan Transit Authority

Exhibit 3

Station Areas and Comparison Neighborhoods



Source: Data assembled from Los Angeles County Metropolitan Transit Authority

Exhibit 4

Average Daily Boardings at Metro Stations, 2013

Line(s)	Boardings
Gold	1,709
Purple and Red	13,555
Red	7,448
All sample stations	6,733

Notes: Only stations included in the study are shown. Purple and Red Lines include stations that serve both lines, as well as the two stations that serve only the Purple Line (Wilshire/Western and Wilshire/Normandie). Union Station, which serves all three lines, is included in the Purple and Red group.
Source: Calculations based on data provided by Los Angeles County Metropolitan Transit Authority

with ridership. The stations with the three highest number of daily boardings are Union Station (over 34,000), which serves the three Metro lines, as well as the Metrolink commuter rail system and Amtrak; 7th St/Metro Center (27,000), serving the three Metro lines and several major bus lines; and North Hollywood (17,000), which connects the Red Line rail to a bus rapid transit system serving the San Fernando Valley. The most used station on the Gold Line is Sierra Madre Villa (2,900), also the line's final station at the time of the study and which (like North Hollywood) has a large adjacent park-and-ride lot. These stations likely attract riders from a larger area than the typical 0.5-mile catchment estimated for walking.[1] Unfortunately we do not have time-series ridership data by station and so cannot determine how much current ridership reflects changes that have taken place since station opening versus original population density or land use.

In an economically efficient world, in order to maximize the value of infrastructure, rail stations should be located in areas with the greatest potential for ridership—based on the density of nearby population and jobs—and with potential for high-density development surrounding stations. In reality, the nearly three-decade-long planning for Metro routes was influenced by numerous competing political factions, including the Los Angeles Mayor and City Council members, Los Angeles County supervisors, members of Congress, city and county taxpayers, neighborhood residents, local business leaders, as well as civic, cultural, and economic institutions throughout the region.[2] The general direction of each line, as well as the placement of some stations, reflect compromises along multiple dimensions. For instance, the Blue Line between Los Angeles and Long Beach was built first because of several political and fiscal advantages. Including Long Beach brought additional local tax revenues into the deal, and using existing rail rights-of-way reduced development costs. The route ran through the district of a highly influential Los Angeles County Supervisor, Kenneth Hahn, and through a largely industrial corridor with mostly low-income residents who generally supported transit, or at least were not organized in opposition to the route (Elkind, 2014). The Green Line was built down the middle of Interstate 105 as part of a consent decree resolving a lawsuit over the freeway's construction (Elkind, 2014). The subway lines from downtown Los Angeles to Hollywood and the San Fernando Valley were the most controversial

[1] Commuters who bike to rail stations may also originate from a larger catchment area.

[2] The lengthy and complex planning and development process was minutely documented in Elkind (2014). Taylor, Kim, and Gahbauer (2009) examined political influences for the Red Line. In this article, we briefly summarize a few of the general factors and examples that illustrate why rail station areas are systematically different than control areas.

routes. Initially, the subway was planned to run along Wilshire Boulevard from downtown Los Angeles in the east to Fairfax Avenue on the west, one of the densest employment and housing corridors in the U.S. However, political opposition from residents of several affluent Westside neighborhoods, and their representatives, Congressman Henry Waxman and Los Angeles City Council member Zev Yaroslovsky, effectively forced the subway to turn north from Wilshire much farther east than originally planned (Elkind, 2014; Taylor, Kim, and Gahbauer, 2009). The final route along Vermont Avenue was selected because it had fewer residential areas to raise opposition and because the subway was supported by several large health and educational institutions along the route (Elkind, 2014). Similarly, the stations in Hollywood were supported by the local chamber of commerce, which welcomed the potential revitalization of a declining area (Elkind, 2014). In general, well-organized opposition by affluent homeowners blocked proposed routes that would have directly connected some of the largest and densest employment centers, resulting in routes through less dense, lower-end commercial and industrial corridors.

Besides the overall level of ridership, composition of Metro rail passengers may affect the potential for economic development near new stations. Higher income riders will have greater potential purchasing power and so increase the demand for housing and other goods and services near rail stations. According to Census data, the median household income of rail transit commuters living in Los Angeles and Pasadena is around $61,000, about $14,000 below incomes for car commuters and well above the $42,000 median income for bus riders. Many of LA Metro's rail passengers had previously relied on buses as a primary means of transportation, prior to the opening of the rail system, so rail represents not an increase in total mass transit share but a switch across modes within transit. In some instances, rail stations were built at locations with important bus connections (for instance, all the Purple Line stops along Wilshire Boulevard are served by the heavily used Metro Rapid 720 express bus). For such station areas, the site's accessibility through public transit may already have been capitalized into land values and development patterns well before the rail stations opened.[3]

Data Sources and Empirical Approach

We analyze changes in employment density and composition around 28 rail stations that opened in Los Angeles County between 1992 and 2003. As a comparison group, we identify a set of intersections located more than 0.5 mile but within 3 miles of the rail stations. The analysis uses several variations on a difference-in-differences framework to test whether employment changed near rail stations after station opening, relative to control areas. We test for differences before and after opening, as well as variation over time before and after opening.

Data Sources

The location and opening dates of rail transit stations were assembled from the LA Metro website and supplemental documentation. The street address of stations has been geocoded and matched to latitude-longitude coordinates and census geographies. Information on which rail lines serve

[3] Unfortunately, we do not have time-varying data on bus station locations and service lines.

each station was also assembled. The research focuses on 28 stations along the Red, Gold, and Purple Lines, for which we have sufficient data on preopening and postopening outcomes.[4]

Data on business establishments come from the National Establishment Time Series, or NETS, database, which contains the business name, address, North American Industry Classification System (NAICS) industry code, and number of employees for all business establishments from 1992 to 2009. Outcomes of interest are the total number of jobs near stations and the mix of jobs by industry category.

General economic and demographic characteristics on station and control areas are assembled from tract-level data from the 1990 and 2000 decennial census and the 2005–2009 American Community Survey. Treatment areas around stations are defined as circles with radius of either 0.25 or 0.5 mile, while control areas are similar-sized circles around major intersections, described in more detail in the following section. To match census tract characteristics to station and control areas, we use GIS to determine the percent of land in each study area drawn from each census tract, and created weighted averages of census variables using these percentages. Variables included in the analysis include population density and median household income.

Empirical Approach

The research design compares changes in housing and employment outcomes near newly opened rail stations, before and after opening. As shown in exhibit 5, study-area stations offer sufficient variation in timing to allow analysis of employment changes prior to and after development. The stations vary along a number of other dimensions that are likely to affect employment outcomes. Some stations are below ground while others are above grade, and they are located in neighborhoods of varying economic, demographic, and physical characteristics. The density and mix of prior development around the station sites also varies. The Red and Purple Lines run through predominantly commercial parts of Los Angeles, as well as some residential areas near North Hollywood, while the Gold Line goes through both residential and commercial areas. About three-fourths of the stations are located within the city of Los Angeles, with six in the city of Pasadena and one in the city of South Pasadena. Treatment areas are defined as circles of either 0.25- or 0.5-mile radius from the rail station, which prior literature has shown is the typical catchment area for rail transit ridership (Guerra and Cervero, 2013; Hess and Almeida, 2007; Kolko, 2011; McDonald and Osuji, 1995). We use 0.25-mile radius for Red and Purple Line stations, because these stations are located closely together, and 0.25 mile yields mostly nonoverlapping treatment areas. The Gold Line stations and Red Line stations in North Hollywood are located farther from one another, so we use 0.5-mile radius as the treatment area for those stations.[5]

[4] The Blue Line stations opened in 1990, before our employment data are available, whereas the Expo Line and some Gold Line stations are too recent for us to observe poststation outcomes. The Green Line is excluded because most stations are in the freeway median, making development immediately adjacent to the stations impossible. Descriptive statistics include all 28 stations, but regression analysis excludes the 5 stations that opened prior to 1996, because we do not observe at least 3 years of preopening employment.

[5] The 0.5-mile treatment areas around three downtown Pasadena stations do overlap, but the 0.5-mile catchment area was deemed more appropriate, given the presence of onsite station parking. The overlapping areas are in a sense doubly treated, which could introduce upward bias into the estimated impact of those stations. A few control areas have small overlaps with the station areas, which may bias results downward for those pairs, but the small number of overlapping control areas is unlikely to influence aggregate regression results.

Exhibit 5

Station Opening Dates

Year Open	Number of Stations	Station Name(s)	Lines
1990	1	7th St/Metro Center	Blue, Purple, Red
1992	1	Union Station	Gold, Purple, Red
1993	3	Civic Center, Pershing Square, Westlake/Macarthur Park	Purple, Red
1996	3	Wilshire/Normandie, Wilshire/ Vermont, Wilshire/Western	Purple, Red
1999	5	Hollywood/Vine, Hollywood/ Western, Vermont/Beverly, Vermont/ Sunset, Vermont/ Western	Red
2000	3	Hollywood/Highland, North Hollywood, Universal City	Red
2003	12	Allen, Chinatown, Del Mar, Fillmore, Heritage Square, Highland Park, Lake, Lincoln/Cypress, Memorial Park, Mission, Sierra Madre Villa, Southwest Museum	Gold
Total	28		

Note: When the 7th St/Metro Center station opened in 1990, only the Blue Line was in operation.
Source: Data assembled by authors from Los Angeles County Metropolitan Transit Authority

The key challenge in determining whether new rail stations lead to changes in nearby economic activity is identifying plausible comparison areas: geographic areas that had similar characteristics to station areas prior to station opening and would have had similar trajectories over time but which were not affected by the new stations. As summarized in Section 2, historical evidence reveals that LA Metro station locations were selected based largely on political and fiscal compromises, which may not correspond to the most economically or geographically efficient sites. Nonetheless, station locations likely differ from all nonstation areas in Los Angeles County in ways that can affect subsequent development. Therefore, we defined comparison areas based on several criteria designed to control for important preopening differences. First, comparison areas should be more than 0.5 mile from any rail station (new, existing, or future) so they will not directly be affected by the station. Second, they should be located within 3 miles of at least one newly opened station, so that they share general place-specific attributes, such as proximity to large employment centers or school districts. Third, because rail stations are almost always located at intersections of major streets, which will have relatively high volumes of car and pedestrian traffic, control areas are selected from among the intersections of similarly sized streets. In practice, we attempted to define control areas as intersections that shared one or more streets with rail stations (for instance, the intersection of Western Avenue and West 3rd Street is a comparison site for the rail station located directly south at Western Avenue and Wilshire Boulevard).

This approach offers two advantages over other matching methods, such as propensity score matching (PSM). First, our treatment areas—circular areas within walking distance of transit stations—do not correspond to conventionally defined geographic areas such as census tracts or block groups. (Indeed, most stations are located at the intersection of multiple census tracts, so any single tract or block group captures only a fraction of the relevant area.) Therefore, no set of predefined geographies not affected by stations could serve as potential control areas to be used in an automated matching process. Second, the underlying rationale for why station areas should see increased economic activity is that they benefit from particularly high accessibility to a larger transit network. The major intersections where stations are located tend to have greater access for automobiles, buses, and pedestrians, as well as trains. Choosing control areas that share similar road access allows us to control for the nonrail access of the comparison sites, in a way that would be difficult to capture accurately using PSM or similar methods.

Exhibits 2 and 3 show the location of the 28 station areas and 48 comparison areas in the study. The stations form a rough triangle among the North Hollywood Station (northwest corner), Sierra Madre Villa Station in Pasadena (northeast corner, approximately 20 miles apart), and the 7th Street/Metro Center Station in downtown Los Angeles (approximately 13 miles southeast of North Hollywood and 15 miles southwest of Sierra Madre Villa). Stations and control areas form several spatial clusters, assigned to five geographic submarkets: Arroyo Seco, Central Los Angeles, Downtown Los Angeles, North Hollywood, and Pasadena.

We begin with a set of graphs and descriptive statistics, illustrating the levels and changes in employment during the study period. We then use a modified difference-in-differences framework to compare station outcomes and comparison area outcomes, as illustrated in equation (1).

$$Y_{it} = \beta_0 + \beta_1 Station_i + \beta_2 Post_{it} + \beta_3 Post{*}Station_{it} + \beta_4 X_{it} + \beta_5 Submkt_j + \varepsilon_{it} \quad (1)$$

In this equation, *i* indexes the study area, *t* indexes the year. *Y* is a measure of employment. *Station* is a dummy indicating station areas. We look at both employment density (employees per acre) across all industry sectors as well as share of employment in each of four broad industry categories: commercial, industrial, public-institutional, and miscellaneous (see the appendix for NAICS two-digit sectors assigned to the four industry categories). *Post* is a dummy variable that equals one after station opening (for comparison areas, this is based on the opening date of the nearest station). The coefficient of interest is β_3, on the interaction between *Station* and *Post*, indicating whether employment near station areas changes after station opening. *X* is a vector of control variables that could influence employment outcomes in study areas and change over time, such as population density and household income. Models also include polynomial terms for year (year and year-squared), to control for larger economic time trends such as labor market conditions.[6] Fixed effects for geographic submarkets described previously are also included.

The before-and-after opening framework may obscure an important question: do employment patterns vary differently across years, either before or after station opening? Several of the hypotheses about how outcomes might vary over time would not be captured by a simple before-and-after analysis. Some studies of new rail lines in other cities have found an "anticipation effect," in which real estate prices near stations increase after the locations have been announced but well before the stations begin operating (Billings, 2011; McMillen and McDonald, 2004). For impacts to begin appearing soon after the announcement, it is necessary that landowners or developers have reasonably certain expectations that stations will indeed be built at the announced locations, in a time frame that justifies current investment.[7] However, in the case of Los Angeles, it is unclear

[6] We include time trends as polynomial terms rather than a set of year fixed effects to avoid collinearity with years of station opening. Robustness checks using linear year and higher order polynomials suggest a squared term is the appropriate functional form.

[7] In Chicago, the line in question was an expansion of the already well-utilized system, adding a connection from downtown to Midway airport (McMillen and McDonald, 2004). In Charlotte, the city government revised the zoning and land use planning to maximize growth potential around a new light rail system (Billings, 2011). In both cases, the announcement of specific locations was followed relatively soon by appropriation of funds and the start of construction.

whether the conditions for anticipatory investment were present. The earliest plans suggesting rail line pathways emerged in the early 1970s, but federal and local funding for construction remained highly uncertain until the mid-1980s. The location of stations along the Red and Purple Lines was highly contentious, with multiple plans proposed and political jockeying for and against, until shortly before construction began (Elkind, 2014). In practice, we are unable to test for changes in employment before and after the announcement date, or around the date that funding was secured, because our employment data do not extend back far enough. Given the demonstrated reliance of Los Angeles commuters on cars, demand for rail transit—particularly for early stations—will be particularly uncertain. Thus it seems plausible that employers or real estate developers may be reluctant to expand employment or construct buildings near a planned station until a few years after operation to observe the volume of transit riders and effectiveness of the new rail line. In this case, there may be a substantial delay before aggregate economic patterns change. To test for varying employment patterns over time, we estimate the following regressions, shown in equation (2).

$$Y_{it} = \beta_0 + \beta_1 Station_i + \beta_2 YrsPre_{it} + \beta_3 Station*YrsPre_{it} + \beta_4 YrsPost_{it} + \beta_5 Station*YrsPost_{it} + \beta_6 X_{it} + \beta_7 Submkt_j + \varepsilon_{it} \qquad (2)$$

In this equation, *YrsPre* is a continuous numeric variable indicating the number of years prior to station opening (equal to 0 for all years after opening), *YrsPost* is the count of years after station opening (equal to 0 for all years prior). The interaction term, *Station*YrsPost*, gives the coefficient of interest, indicating the difference in employment associated with each year after opening for station areas, relative to control areas. Regressions include the same control variables, year polynomial terms, and fixed effects for geographic submarkets.[8]

The regression analysis implicitly tests the hypothesis that increases in land values due to station areas' improved accessibility will result in higher density of economic activity. However, localized public policy interventions, particularly land use regulation, have the potential either to enhance or constrain market pressures on economic outcomes near stations. For instance, if new stations are opened in areas zoned for low-density, exclusively residential land use, then it is unlikely that new housing or employment could emerge near the station, even if firms and developers wished to locate nearby. Alternatively, if zoning grants developers density bonuses or other incentives to locate near stations, relative to equivalent sites not near transit, then the regulation could result in more economic activity near the station than markets alone would have provided. Because zoning and other public interventions may either constrain or enhance development, and prior research has found that zoning differs substantially across LA Metro stations (Schuetz, Giuliano, and Shin, 2017), it seems likely that not controlling for local policies will introduce measurement error but will not consistently bias our results.

Results

The locations in which new rail stations were built during the 1990s and 2000s had unusually high employment densities prior to station opening. Employment densities around station and

[8] As a robustness check, we also estimate regressions with a full set of dummy variables for each year before and after opening. Results of the fully interacted model are substantively similar to the simpler interactions with continuous number of years; results available from authors on request.

control areas fluctuated somewhat over time with macroeconomic cycles, but there is no clear time trend. Descriptive statistics and regressions both indicate that station areas did not see employment growth within 3 years before or 5 years after station opening. Regression results suggest that a few stations that opened between 1996 and 1999 saw significant employment gains between 5 and 10 years after stations opened.

Descriptive Statistics: Employment Metrics

A substantial difference between the rail system in Los Angeles and those in older cities such as New York City and Boston is that land use and employment patterns were well-established before Los Angeles' rail stations were built. As noted in the second section, rail lines were intended to connect existing employment centers, enhancing access of potential workers to job-rich areas. An analysis of preopening station area characteristics confirms that areas where rail stations opened during the 1990s and 2000s already had high employment densities well before the rail network was built (exhibit 6). The average station area had nearly 70 employees per acre as of 1992, four times the employment density in control areas; excluding stations and control areas in downtown Los Angeles, station areas had on average 34 employees per acre, compared to 11 employees per acre in control areas. Both station and control areas had much higher employment density than Los Angeles County overall, suggesting that the selected control areas form a better counterfactual to station areas than the remainder of the county. Establishments near future stations were, on average, nearly 50 percent larger than establishments in control areas, measured by employees per establishment. Station and control areas share two prominent employment sectors: retail (NAICS codes 44 and 45) and healthcare and social assistance (NAICS code 62) each make up 10 to 12 percent of employment. Beyond those sectors, employment near stations was more weighted

Exhibit 6

Station and Control Areas Prior to Rail System Opening, 1990

	Station Areas	Control Areas	Los Angeles County
Employment characteristics			
Employees per acre	66.6	15.8	1.5
Establishments per acre	3.49	1.57	0.1
Employees per establishment	21.3	14.6	11.6
Employment mix			
Commercial (%)	47.0	41.0	38.1
Industrial (%)	22.7	33.9	37.2
Public/institution (%)	20.1	18.5	19.0
Miscellaneous (%)	7.2	7.8	5.8
Population characteristics			
Population per acre	111.8	102.3	3.4
Household income ($)	44,017	58,187	75,908
Bachelor's/graduate degree (%)	22.5	23.6	22.3
Black (%)	9.0	9.4	11.2
Hispanic (%)	42.9	42.2	37.3
Asian (%)	16.4	14.4	10.5
Younger than 18 (%)	20.31	22.98	26.2

Notes: All numbers for station and control areas are averages per study area. Housing and census variables are measured as of 1990, employment variables as of 1992–1994. Prices and incomes reported in constant 2009 dollars.

Sources: Calculations based on National Establishment Time Series database, DataQuick, and American Community Survey 2005–2009 toward commercial sectors, including professional, scientific and technical services, and accommodation/food services, which are typical users of retail and office buildings. Control areas leaned more toward industrial sectors, mostly wholesale trade and manufacturing, which tend to be located in buildings with lower floor-to-area ratios.

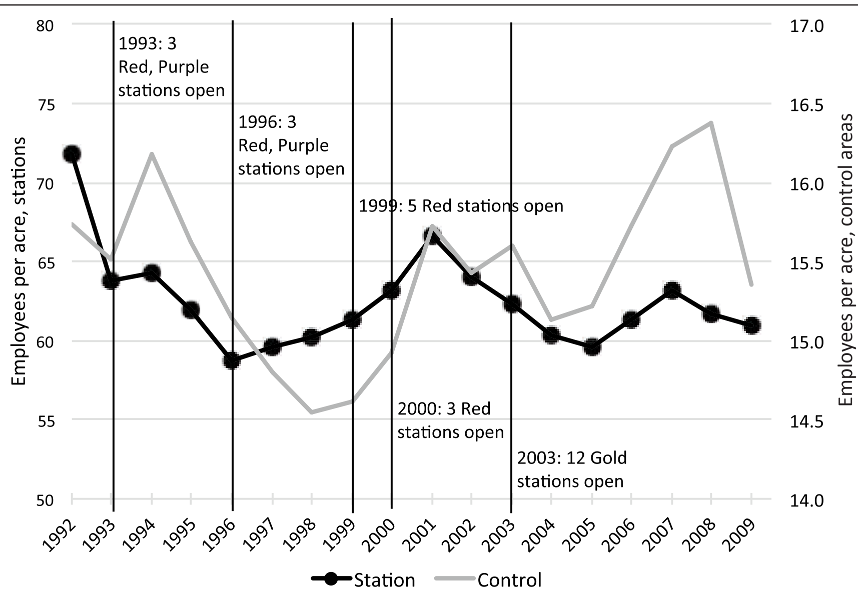
Station and control areas differed somewhat in population characteristics, prior to development of the rail network, but these differences are less pronounced than the prestation differences in employment. Both station and control areas had higher population densities than Los Angeles County overall. As of 1990, residents near station areas had lower incomes than the population in control areas and the county overall. The populations in both station and control areas tended to be slightly more Hispanic and Asian than Los Angeles County, with slightly lower African-American population shares.

The implications of these differences for future job growth are not immediately obvious. It is possible that the more industrially oriented control areas will be less desirable for additional development, or may not be zoned for standard commercial uses. Alternatively, areas with more industrial uses might offer more large-scale land parcels for redevelopment, or face less opposition from existing landowners and tenants at the prospect of new, higher-density development. Lower incomes in station areas may suggest that those areas were initially less attractive sites for new development, or that residents would welcome additional jobs and services. Thus, it is unclear whether and in what direction preexisting differences might bias regression results.

Exhibit 7 shows average employment density near station and control areas over time, indicating years in which groups of stations opened. Because stations opened intermittently over a relatively long period that includes several business cycles, we try to distinguish the effect of the stations

Exhibit 7

Employment in Study Areas, 1992–2009

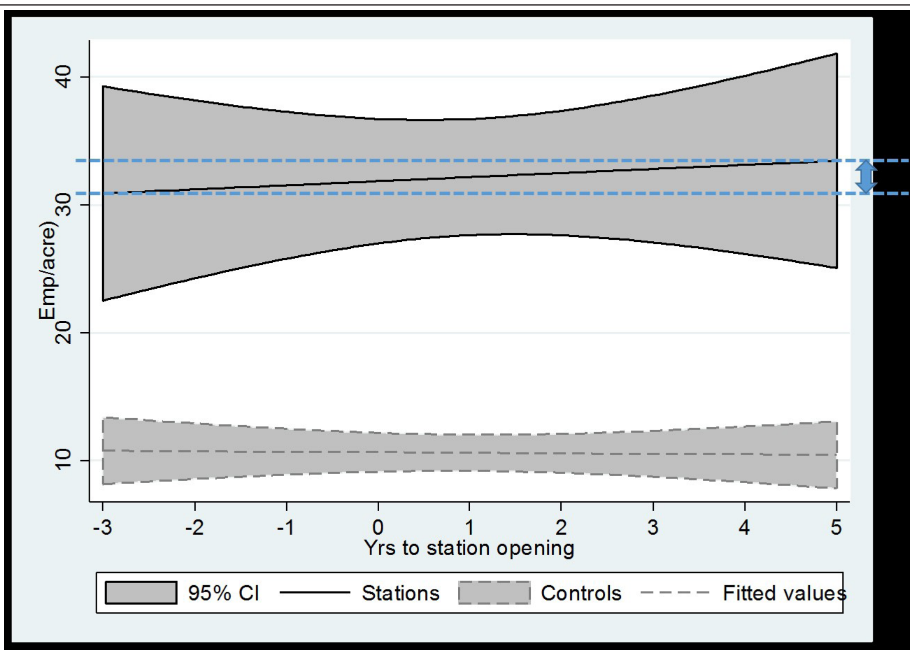


Source: Calculations based on National Establishment Time Series database from changes in general economic conditions. Average employment densities in both station and control areas show some cyclical movements between 1992 and 2009, decreasing during the recessions of the early 1990s, early 2000s, and in the Great Recession from 2007 to 2009 (exhibit 7). These cyclical variations generally match time trends in employment density for Los Angeles County as a whole. However, there is no clearly apparent time trend among the study areas, nor does the graph show clear visual evidence of employment changes around station opening dates.

To focus more clearly on the time periods of interest, exhibit 8 shows average annual employment density, beginning 3 years before station opening and ending 5 years after station opening. The employment analysis includes only the 23 stations and matched control areas for which at least 3 years of preopening employment data are available.[9] The year of opening is defined for each station/control area, so that t_0 represents different years for each cluster of stations/controls. Although average employment density levels differ substantially between stations and control areas, the time trends before opening are quite similar; employment is virtually flat during the prestation years and for 1 year afterward (exhibit 8). Station areas show a modest increase between years 2 and 5, from about 32 employees per acre to about 34 employees per acre. Control areas have flat employment

Exhibit 8

Employment Density, Before and After Station Opening



CI = confidence interval.
Notes: Average values and 95-percent confidence intervals for station and control areas. Excludes three stations that opened in 1993 and matched control areas.
Source: Calculations based on National Establishment Time Series database

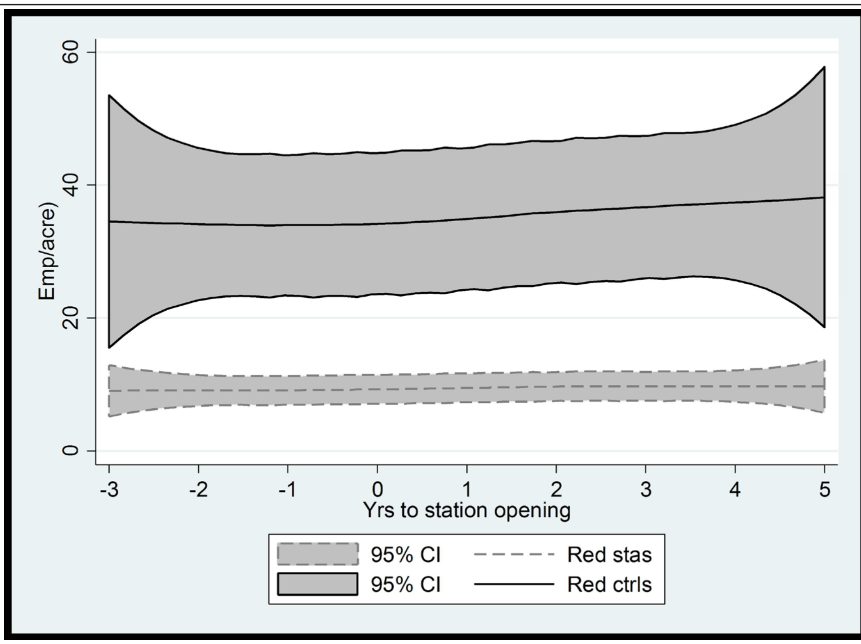
[9] Dropping the three earliest Red and Purple Line stations reduces the average employment density among stations by roughly one-half, from about 60 employees per acre to about 30, because the earliest stations include the highest density employment centers in downtown Los Angeles.

density through year 3 after station opening, then an increase of slightly less than 1 employee per acre from years 3 through 5. Both station and control areas have fairly wide 95-percent confidence intervals around the estimated line, suggesting that the slopes are not significantly different than 0.

The three rail lines in our sample differ by opening year, and run through different parts of the city, so the averages for all stations may conceal differences in time trends across lines. Exhibits 9 and 10 show employment density before and after opening for stations and controls along the Red and Gold Lines.[10] Employment densities around Red Line stations and controls are trending slightly upward during the 8-year window around station opening, but the slopes are not significantly different from one another, and there is no indication of a change in slope after opening (exhibit 9). Gold Line stations have employment densities close to their control areas, and show different time trends; employment is trending upward around station areas and downward near control areas (exhibit 10). However, the confidence intervals for both station and control areas are quite wide and almost completely overlap, so we cannot infer significant differences between them from the graphs. Neither stations nor controls show changes in slope after station opening. Replicating exhibits 8 through 10 for longer time intervals show similar patterns (results available from authors by request).

Exhibit 9

Employment Density Around Red Line Areas, Before and After Station Opening

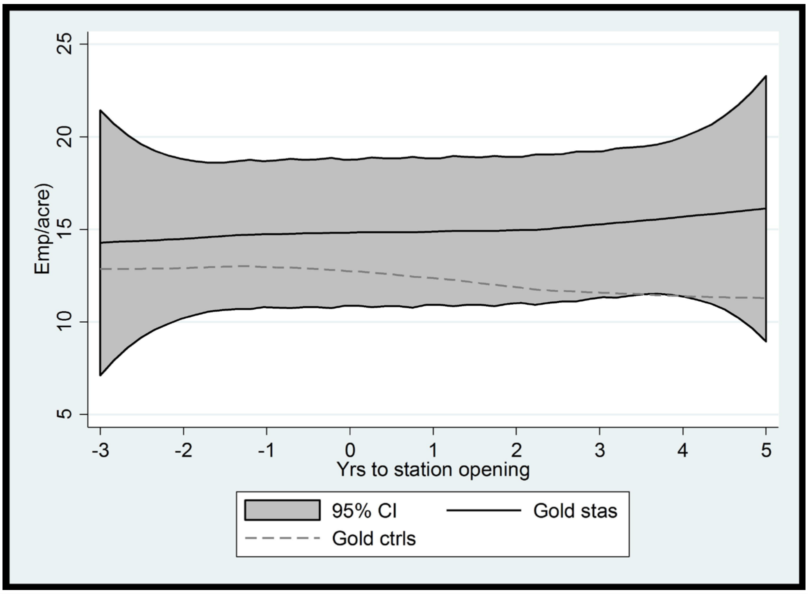


CI = confidence interval.
Notes: Average values and 95-percent confidence intervals for station and control areas. Excludes three stations that opened in 1993 and matched control areas.
Source: Calculations based on National Establishment Time Series database

[10] Only three stations on the Purple Line have 3 years of preopening employment data.

Exhibit 10

Employment Density Around Gold Line Areas, Before and After Station Opening



CI = confidence interval.
Notes: Average values and 95-percent confidence intervals for station and control areas. Excludes three stations that opened in 1993 and matched control areas.
Source: Calculations based on National Establishment Time Series database

Before estimating regressions, we compare our main employment outcomes for the 3 years before and after station opening. We calculate average employment density and share of employment in each of the four industry categories for station and control areas over 3 years, before and after opening (exhibit 11). Using a 3-year window allows for the possibility that employment patterns might begin changing prior to opening due to anticipation, or that it changes might take several years after opening to become evident.[11] None of the five employment outcome variables show significant changes from the 3 years prior to station opening to the 3 years after opening, either in station or control areas. Among station areas, there are small increases in employment density, commercial employment share, and public/institutional employment share, but none of these differences are statistically different from 0 or substantively large in magnitude. The largest change is a nearly 3-percentage-point decrease in industrial employment share, but this is also not statistically significant. Among control areas, overall employment density is essentially the same before and after opening years of the matched station areas, and there are no significant changes in employment composition. Consistent with exhibits 7 through 10, results indicate substantially higher employment levels around stations than in control areas, but do not indicate changes in employment levels shortly after station opening.

[11] We have examined annual data for these intervals separately for each station and for groups of stations that open in the same year, because the impact of opening might vary across points in the economic cycle. No observable time trends are within the 3-year windows, nor does apparent variation occur in time trends across stations. The annual data are reasonably smooth, not displaying large year-over-year variations that would raise concerns about short-term noise-to-signal ratios. Therefore, the remaining analysis will use annual employment metrics to allow for clean identification of before-and-after periods.

Exhibit 11

Employment Changes, Before and After Station Opening

	Station Areas			Control Areas		
	Preopening	Postopening	Difference	Preopening	Postopening	Difference
Employment density, all sectors	31.5	32.0	0.47	10.6	10.6	– 0.07
	(4.0)	(4.0)		(1.0)	(0.9)	
Commercial (%)	47.5	49.5	1.97	46.6	47.2	0.55
	(2.4)	(2.1)		(1.9)	(1.9)	
Public/institution (%)	21.8	22.7	0.82	22.0	22.3	0.31
	(2.4)	(2.2)		– (1.7)	– (1.8)	
Industrial (%)	22.5	19.7	– 2.77	22.9	22.3	– 0.62
	(1.3)	(1.2)		(1.4)	(1.1)	
Miscelleaneous (%)	8.1	8.1	– 0.03	8.5	8.2	– 0.24
	(0.5)	(0.6)		– (0.8)	– (0.7)	
n	69	69		117	117	

Notes: Excludes five stations that opened before 1996 and nine matched control areas, because authors cannot observe 3 years of preopening employment. Standard errors shown in parentheses. None of the differences are statistically significant at the 10-percent level or above.

Regression Results: Employment Changes

As a more rigorous test of whether employment around stations changed after stations opened, we estimate a series of regressions summarized in exhibit 12. We estimate preopening and postopening differences for three time windows: (1) 3 years before station opening to 5 years after, (2) 5 years before to 10 years after, and (3) using the entire set of years available in the dataset. Stations that opened prior to 1996 are excluded from the regression analysis, because we do not observe preopening employment.[12]

Regression results generally confirm the findings from graphs and descriptive statistics: station areas had higher initial employment density than control areas, and saw no immediate changes in employment following station openings. However, there is some evidence that employment may increase in the 5- to 10-year window after stations open. In the simple before-and-after analysis (columns 1 through 3), the coefficient on *Post*Station* increases in magnitude as the time window around station opening expands, only becoming statistically significant when including all years (column 3). The magnitude suggests a 34-percent increase in employees per acre (from an average of 67 prior to opening) over the entire duration of poststation years. However, we can only observe 10 years of postopening employment for eight stations, up to 9 years of postopening employment for another three stations, while we observe at most 6 years of postopening employment for the 12 Gold Line stations. This suggests that the employment gains discerned in the regression occur for the stations that opened from around 1996 to 1999, and became evident toward the latter part of the study period. Because that period coincides with the Great Recession, it may in fact be that those station areas lost less employment during the downturn than control areas, rather than experienced absolute employment gains.

[12] Estimating the regressions for variations on these time windows, including 3 years prior to opening to 5 or 10 years after opening yields very similar results. Including stations that opened prior to 1996 does not alter the estimated coefficients but is conceptually less clean.

Exhibit 12

Regression Results on Employment Density, Before and After Station Opening

Dependent Variable	ln(Employees/Acre)			ln(Employees/Acre)		
	(1)	(3)	(4)	(5)	(7)	(8)
Time window	$-3 \le t \le 5$	$-5 \le t \le 10$	All yrs	$-3 \le t \le 5$	$-5 \le t \le 10$	All years
Station	0.906***	0.857***	0.663**	0.883***	0.842***	0.850***
	(0.254)	(0.250)	(0.257)	(0.251)	(0.261)	(0.259)
Post	0.079	– 0.002	– 0.100			
	(0.171)	(0.150)	(0.110)			
Post*station	– 0.030	0.112	0.344**			
	(0.056)	(0.084)	(0.143)			
YrsPre				– 0.052	-0.038	– 0.007
				(0.089)	(0.086)	(0.085)
Station*YrsPre				0.014	– 0.003	– 0.0511**
				(0.016)	(0.015)	(0.021)
YrsPost				0.036	0.038	0.046
				(0.089)	(0.085)	(0.083)
Station*YrsPost				– 0.004	0.0411**	0.0563***
				(0.011)	(0.020)	(0.018)
Group fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	558	872	1,116	558	872	1,116
R-squared	0.296	0.321	0.299	0.297	0.327	0.312

*** $p < 0.01$. ** $p < 0.05$. * $p < 0.1$.

Notes: All models include year and year-squared, log of population density and income, and group fixed effects. Robust standard errors, clustered by study area, in parentheses.

Next we estimate a parallel set of regressions using continuous number of years before and after station opening (exhibit 12, columns 4 through 6). Results are very similar to those using a binary indicator for after opening: the coefficient on *Station*YrsPost* does not become positive and significant until the study window includes up to 10 years after opening (column 5), and increases in both magnitude and significance when using the full set of years (column 6). The magnitudes of the coefficients suggest a 4- to 6-percent increase in employment per acre each year after opening, with most of this coming from the early-opening stations in the 5 to 10 years afterward. These annual numbers are roughly consistent with the 34-percent increase for all poststation years from column 3.

The example of the Hollywood and Vine station on the Red Line illustrates why development may substantially lag station opening. The Los Angeles Community Redevelopment Agency used eminent domain to assemble parcels near the station, enabling LA Metro to undertake a large-scale redevelopment project, complete with high-density multifamily housing, a hotel, and ground-floor commercial uses (Schuetz, Giuliano, and Shin, 2017). Even with unusually concerted efforts by public agencies, the redevelopment project was completed in 2009, 10 years after the station opened. This example raises questions about how quickly redevelopment may become apparent in aggregate data. Because we only observe 10 years of postopening data for a few stations, we cannot infer whether the lag reflects true redevelopment times or some unobserved characteristics for the particular set of stations. Similar regressions that estimate employment density separately for the Red and Gold Lines, and by geographic submarket, yield no significant results on *Post*Station*, even among the oldest station clusters in Central Los Angeles and North Hollywood (results available from authors upon request).[13]

[13] These regressions were estimated for Central Los Angeles, North Hollywood, Arroyo Seco, and Pasadena submarkets. Only one station in downtown Los Angeles opened after 1996, so we exclude the DTLA cluster.

While employment levels may adjust slowly because of the time needed to construct or reconfigure buildings, the composition of employment across industries could adjust more rapidly using existing space. Therefore we estimate a set of regressions on the employment shares across four industry categories, over 5- and 10-year windows after station opening (exhibit 13). The coefficients from 3 years before to 5 years after opening (columns 1 to 4) show similar results to the difference-in-means tests shown in exhibit 11. During the immediate 5-year period after station opening, employment in station areas shifted toward commercial and public/institutional jobs, away from industrial and miscellaneous sectors, although the changes are not significantly different from control areas. Over the longer time period, up to 10 years after station opening, there were significant gains in public/institutional employment shares relative to control areas, at the expense of employment in the other three industry categories (although none of the negative coefficients are statistically significant). One possible explanation for this shift in overall employment composition is that public sector organizations near stations, including medical facilities and schools, had relatively smaller employment losses during the Great Recession than private sector firms. These results also may indicate greater public investment around stations; for example, new buildings for the California Transportation Department and the Los Angeles Police Department were constructed around the Civic Center station after station opening.

Exhibit 13

Employment Density, by Industry Category

Dependent Variable	Percent of Employees in Industry Category							
Time Window	t-3 to t+5				t-5 to t+10			
Industry Category	Commercial	Public/ Institution	Industrial	Miscellaneous	Commercial	Public/ Institution	Industrial	Miscellaneous
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Station	5.56	– 1.62	– 2.84	– 1.10	8.324*	– 4.09	– 3.06	– 1.18
	(4.85)	(5.71)	(3.55)	(1.93)	(4.65)	(5.44)	(3.37)	(1.69)
YrsPre	0.86	– 1.94	0.74	0.35	0.49	– 2.03	1.32	0.22
	(1.57)	(1.58)	(1.10)	(0.85)	(1.57)	(1.57)	(1.02)	(0.85)
Station*YrsPre	0.26	– 0.37	0.17	– 0.06	– 0.50	0.60	– 0.15	0.05
	(0.50)	(0.58)	(0.47)	(0.28)	(0.41)	(0.48)	(0.40)	(0.20)
YrsPost	– 0.90	1.37	– 0.05	– 0.42	– 0.65	0.96	0.04	– 0.35
	(1.53)	(1.56)	(1.09)	(1.21)	(1.57)	(1.62)	(0.98)	(0.85)
Station*YrsPost	0.66	0.07	– 0.55	– 0.04	– 0.61	1.171**	– 0.49	– 0.07
	(0.59)	(0.54)	(0.49)	(0.33)	(0.44)	(0.57)	(0.38)	(0.21)
Observations	558	558	558	558	872	872	872	872
R-squared	0.237	0.158	0.129	0.111	0.226	0.154	0.122	0.118

*** $p < 0.01$. ** $p < 0.05$. * $p < 0.1$.

Notes: All models include controls for population density, income, year and year-squared, and group fixed effects. Robust standard errors, clustered by study area, in parentheses.

Conclusions and Policy Implications

The Los Angeles metropolitan area is one of several U.S. regions that have recently made substantial public investments in subway or light rail systems. Developing new transit infrastructure can have multiple goals, including increasing access to existing job centers or public facilities, encouraging high density housing near transit and retail, reducing the growth of vehicle traffic and road congestion, and spurring physical and economic development. In this article, we examine how employment patterns have changed around newly opened rail stations in Los Angeles during the last two decades. Although this study focuses on Los Angeles, the results are likely to be relevant to transit planners who are building or expanding rail networks (including streetcars) in cities with similar urban environments, particularly with low transit ridership, multiple employment subcenters, and a densely built urban core.

Results indicate that employment densities in station and control areas fluctuated somewhat over time with regional economic cycles, but there are few clear time trends among study areas. Station areas did not see stronger employment growth within the first 5 years after station opening, but a small group of stations that opened between 1996 and 1999 saw significant employment gains between 5 and 10 years after stations opened.

The relatively scattershot and delayed employment gains near stations most likely reflect two features of the LA Metro system. First, rail transit ridership in Los Angeles is quite low, relative to other large U.S. cities. Due to complicated political considerations that drove the route planning—and perhaps the need to avoid established residential neighbors who opposed the rail—Los Angeles's rail stations were located in areas with high initial job density, although the system did not create direct connections to important job centers on the city's west side. The polycentric employment structure in the Los Angeles metropolitan area makes it difficult for most households to complete the home-to-work journey entirely by rail, therefore it is unclear that most rail stations increase neighborhood accessibility and will result in higher land values. The employment gains around Red and Purple Line stations 5 to 10 years after opening also coincides roughly with the opening of the Gold Line. It is possible that proximity to the older stations became more valuable once the Metro system expanded.

Second, many of the stations are located in densely developed areas with highly fragmented land ownership, so that large-scale redevelopment will require complex and costly land assembly, which adds to the uncertainty and time needed for development. Relative to the legacy systems in New York City and Boston, or even systems like Washington, D.C.'s Metro and San Francisco's BART, LA Metro stations may be too new for land use patterns to have adjusted. The example of the Hollywood and Vine station suggests that, even in areas with strong market demand and TOD-friendly zoning, it may take a decade or more for changes to land use patterns and physical development to emerge.

One potentially important factor our study cannot address is the role of zoning or other localized policy interventions in facilitating development around stations. A parallel qualitative study reveals that the type and density of buildings allowed under zoning varies substantially across sample stations (Schuetz, Giuliano, and Shin, 2017). High-density residential and commercial uses consistent with TOD are allowed near all stations in downtown Pasadena and some parts of downtown and central Los Angeles, but many stations have complex or ambiguous zoning that may hinder redevelopment. Los Angeles and Pasadena also demonstrate fundamentally different approaches to land use planning near transit stations. Pasadena adopted new, density-friendly zoning around all its downtown station areas around the time that Gold Line service began. By contrast, Los Angeles has conducted only piecemeal rezoning or granted variances around selected stations, and those changes were not always implemented when stations opened. More recently, LA Metro has begun a TOD Planning Grant program to help local governments revise their land use regulations around stations in ways that can accommodate and encourage development.[14] This offers one alternative way to coordinate zoning and infrastructure development across multiple agencies; evaluating its effectiveness will be an interesting area for future research.

The experience of Los Angeles offers two key lessons for policymakers in other regions. First, even if rail networks generate long-run economic spillovers to surrounding areas, short-run impacts may be quite limited, especially in regions without strong public transportation usage. Second, transit infrastructure may be intended to serve multiple goals, each of which implies different strategies for station location, coordinating policies, and metrics of success. For instance, if the primary goal is to facilitate access of workers to existing jobs, then stations should be located near large employment centers and near dense residential areas with high proportions of workers who commute to those employment centers. However, residential and commercial areas with high prior density may offer less potential (or require more time) for additional development. If the primary goal is to encourage more or denser residential development, then placing stations in greenfields areas and revising the nearby zoning to allow dense mixed-use development may be a more effective location strategy. Realistically, however, Los Angeles' example suggests that political feasibility may be at least as important as economic efficiency in driving both station placement and coordinating land use policies.

Appendix

Exhibit A-1

Industry Categories, by Two-Digit NAICS Code

Category	NAICS Sector	NAICS2
Commercial		
	Retail trade	44
	Information	51
	Finance and insurance	52
	Real estate and rental and leasing	53
	Professional, scientific, and technical services	54
	Management of companies and enterprises	55
	Arts, entertainment, and recreation	71
	Accommodation and food services	72
Industrial		
	Mining	21
	Utilities	22
	Construction	23
	Manufacturing	31
	Wholesale trade	42
	Transportation and warehousing	48
	Administrative and support and waste management and remediation	56
Public/Administrative		
	Educational services	61
	Health care and social assistance	62
	Public administration	92
Miscellaneous		
	Agriculture, forestry, fishing and hunting	11
	Other services	81

NAICS = North American Industry Classification System.

[14] https://www.metro.net/projects/tod/.

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Authors

Jenny Schuetz is a David M. Rubenstein Fellow at the Brookings Institution.

Genevieve Giuliano is the Margaret and John Ferraro Chair in Effective Local Government at the University of Southern California.

Eun Jin Shin is an assistant professor at the Yale-NUS College.

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Departments

In this issue—

- *Data Shop*
- *SpAM*
- *Evaluation Tradecraft*
- *Correction*

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 david.a.vandenbroucke@hud.gov for consideration.*

First-Time Homebuyers: Toward a New Measure

Arthur Acolin
University of Washington

Paul Calem
Federal Reserve Bank of Philadelphia

Julapa Jagtiani
Federal Reserve Bank of Philadelphia

Susan Wachter
University of Pennsylvania

Abstract

Existing data sources show divergent estimates of the number of homes purchased by first-time homebuyers as a share of all home purchases. In this article, we use a new dataset to construct a time series of the share of first-time homebuyers. This series, based on the Federal Reserve Bank of New York Equifax Consumer Credit Panel, shows a significant decline in the share of first-time homebuyers, particularly among young households, consistent with the decline in homeownership in this age cohort since the early 2000s.

Introduction

The rate of homeownership in the United States has declined since the financial crisis and recession of 2007 through 2009. As of the third quarter of 2017, the U.S. homeownership rate was 63.9 percent, substantially below its peak of 69 percent in 2004 and near a 50-year low. The decline in homeownership is particularly pronounced among young and minority households (Acolin, Goodman and Wachter, 2016). No disagreement exists on the measurement of this decline, which is based on census data reported quarterly (U.S. Census Bureau, 2017).[1] Disagreement does exist, however, on an important component of aggregate homeownership: first-time homebuyers as a share of all purchasers.

The estimated number of first-time homebuyers is an important statistic because it provides data on initial access to homeownership for those who may be renters or living with their parents. It also has implications for future economic activity in the housing sector because households typically move from rentals to starter homes and then to larger homes over the life cycle. Nonetheless, no comprehensive data source is currently available on the number or share of first-time homebuyers in the United States. These statistics are not measured in the decennial census, the annual American Community Survey (ACS), or the monthly Current Population Survey (CPS). A measure of first-time homebuyers exists in the biennial American Housing Survey (AHS) but is limited by the AHS sampling frame and thus cannot be used to identify changes over time for the U.S. market in aggregate.[2] In the absence of census data, two alternative data sources have been developed and used to provide updates on first-time homeownership trends. These data sources report divergent trends in the share of first-time buyers.

The first source is a measure developed by the American Enterprise Institute (AEI) and the Urban Institute (UI) based on mortgage origination data, which shows no decrease since the subprime mortgage crisis. The second source, a survey developed by the National Association of Realtors® (NAR), finds a substantial decrease in the share of first-time homebuyers over time. The AEI/UI measure provides data on the share of first-time homebuyers among users of agency debt, and the NAR measure uses the share among all purchasers, including cash purchasers. In this article, we develop a new measure of first-time homebuyers, using all sources of mortgage funding. Using this measure, we compare, over time, the use of mortgage debt for first-time purchases of homes by age group and by credit score characteristics of borrowers.

We make use of the Federal Reserve Bank of New York Equifax Consumer Credit Panel (CCP), which has been developed with the goal of tracking credit usage, including the use of mortgages in the aftermath of the 2007 subprime crisis (Lee and Van der Klaauw, 2010). This dataset consists of a nationally representative 5-percent sample of credit records.

Using the CCP, we measure the number of first-time homebuyers during the 2002-through-2015 period by identifying borrowers who previously did not have a mortgage and combine this

[1] Available at http://www.census.gov/housing/hvs/data/histtabs.html.

[2] Including a question about first-time homebuyers in the ACS, the CPS/Housing Vacancy Survey, or both would provide a source of reliable estimates. In its absence, the challenges in estimating the number of first-time homebuyers are similar to those faced in obtaining a reliable measure of household formation (Masnick, Giordmaina, and Belsky, 2010; McCue, Masnick, and Herbert, 2015).

measure with U.S. Department of Housing and Urban Development (HUD) data on all home purchases to derive a measure of the trend in first-time homebuyers as a share of overall purchases over time.

The rest of the article is organized as follows. In the following section, we review homeownership shares and first-time homebuyer shares among all home purchasers, based on measures developed in previous studies. The subsequent section applies the new measure of first-time homebuyers using the CCP, to reconcile the different measures of first-time homebuyers, and relates the findings to changes in the funding sources for access to homeownership. The conclusion follows.

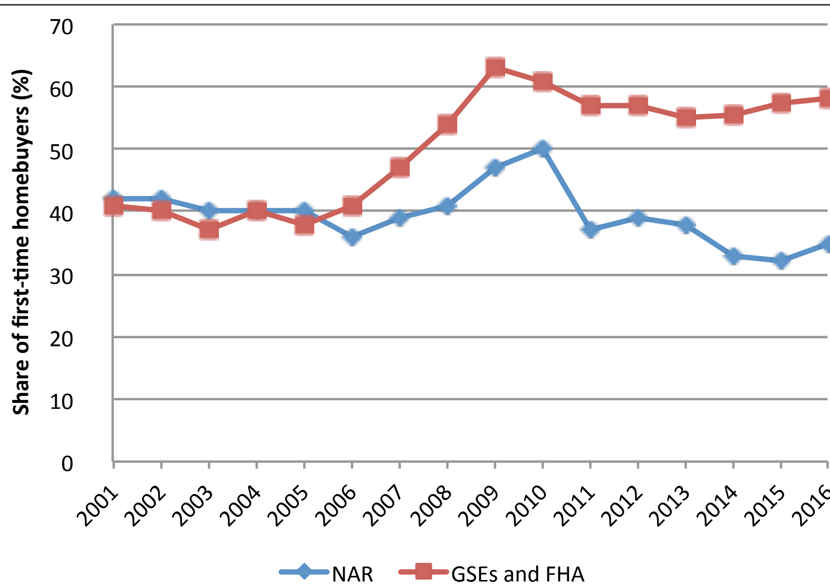
First-Time Homeownership Trends: Measurement Over Time

Exhibit 1 provides time series data on the share of first-time homebuyers from the two widely used existing measures, (1) the NAR survey-based data and (2) the composite data from the government-sponsored enterprises (GSEs) Fannie Mae and Freddie Mac and from the Federal Housing Administration (FHA), which AEI and UI have used to report on first-time homeownership trends (American Enterprise Institute, 2015; 2017; Bai, Zhu, and Goodman 2015).

The two series provide broadly similar measures from 2001 to 2005, with first-time homebuyers relatively constant at about 40 percent of overall homebuyers. The NAR measure shows a decrease in first-time homebuyer share in 2006. Both measures exhibit increases after 2006, which continue until 2009 (AEI/UI) or 2010 (NAR), although the NAR trend line increases less. After that, major

Exhibit 1

Comparison of the Measures of the Share of First-Time Homebuyers



FHA = Federal Housing Administration. GSE = government-sponsored enterprise. NAR = National Association of Realtors®.
Sources: NAR; Federal Housing Finance Agency; FHA

differences emerge in the reported trends of first-time homebuyer share. The AEI/UI estimate shows the share of first-time homebuyers currently far above the 40-percent rate that prevailed before the housing market downturn, to rates of about 60 percent, with peaks of 63 percent in 2009 and 58 percent in 2016. The NAR measure shows the share of first-time homebuyers peak at 50 percent in 2010, but then decrease to a near 30-year low of 32 percent in 2015, increasing to 35 percent in 2016. As of 2016, the difference between the NAR and the AEI/UI measures is 23 percentage points.

These measures diverge due to differences in data sources and methodology used to identify first-time homebuyers. As noted, the NAR measure relies on survey results of all buyers. NAR sends a questionnaire to a random sample of primary resident homebuyers within the previous year (for example, home purchases between June 2014 and June 2015 for the 2015 results). The survey based on all purchase transactions includes both cash transactions and mortgage transactions.[3]

The measure AEI and UI use relies on historical monthly data from Fannie Mae, Freddie Mac, and FHA. The data include mortgages sold to the GSEs and mortgages covered by FHA mortgage insurance. Purchases made with mortgages held in lenders' portfolios, cash purchases, and noninstitutional privately transacted mortgages are not included.[4]

With the disappearance of subprime lending and withdrawal of private securitization from the mortgage market after 2006, first-time homebuyers became concentrated in the FHA, Fannie Mae, and Freddie Mac segments of the mortgage market (with jumbo loans concentrated in the bank portfolio segment). Thus, the FHA, Fannie Mae, and Freddie Mac segments became less representative of the market as a whole and would be apt to overstate the share of first-time homebuyers. In addition, as Urban Institute (2016) pointed out, the exclusion of cash transactions in the AEI/UI measure increases the reported share of first-time buyers relative to the NAR estimate because first-time homebuyers are less likely to be cash buyers.

The CCP Data on First-Time Homeownership

Almost all first-time homebuyers use debt. A comprehensive measure of the share of first-time homebuyers using mortgage debt can be constructed using the Federal Reserve Bank of New York Equifax CCP. The CCP provides a broad measure of first-time homebuyers who use mortgage debt. The CCP dataset also includes individual characteristics such as age, credit score, and information about household-level credit and debt—including second-lien mortgages, credit cards, automobile loans, and student loans—and thus can be used to analyze the relationship among different uses of debt and access to homeownership using a mortgage.

[3] The survey is restricted to principal residence purchases only; it does not include investor or vacation homes. For the 2016 "Profile of Home Buyers and Sellers," NAR mailed a survey to a random sample of 93,171 recent homebuyers who had purchased a home between July 2015 and June 2016. Of the responses received, 5,465 responses were from primary residence buyers, resulting in an adjusted response rate of 5.9 percent after accounting for undeliverable addresses (National Association of Realtors®, 2016).

[4] The Federal Housing Finance Agency first made these historical databases available to the public in 2013. In the data, first-time homebuyers are defined as those individuals who did not own a property with a mortgage within the past 3 years (FHFA, 2013).

The CCP provides quarterly detailed credit report data dating back to 1999[5] for a 5-percent representative random sample of individuals with at least one credit record. The random selection of the database is based on consumers with a Social Security number (randomizing the last two digits of the Social Security number). The database follows the characteristics and credit performance for these 5 percent of randomly selected consumers (so-called Primary consumers) for the entire data period (until their death or bankruptcy filing, resulting in no credit record for at least 6 months). In addition to data on the Primary consumers, the CCP also reports characteristics and credit performance of all the consumers who live in the same household (same address) as the Primary consumers (although their characteristics would stop being reported once they moved out of the Primary consumer's household). The dataset of the consumer-quarter panel is not a balanced panel—exits occur due to factors such as young adults acquiring a credit record and death.

This longitudinal panel of individuals and households makes it possible to identify households that have taken out a mortgage and did not have one previously. We focus on the household level because the Primary consumers in the CCP may not be the head of the household (and thus would not have mortgage debt), but others in the household who may not be the Primary consumer would have mortgage debt. In addition, when the head of the household passes homeownership on to another household member, we also capture that it is not a new homebuyer. Using the CCP dataset, we identify first-time homeownership with a household that obtains a mortgage in a given quarter and shows no mortgages reported in its credit file during the previous 3 years.[6] The 3-year prior observation window is similar to the one used in the AEI/UI measure. Note that some households identified as first-time homeowners by this criterion may have owned a home but did not have a mortgage (originally having purchased the home with cash or having already paid it off), but such cases should be relatively infrequent.

The CCP provides information about the number of new homebuyers using a mortgage but not about the total number of home purchase transactions regardless of whether they involved a mortgage. Therefore, we use HUD estimates about new and existing homes sold (HUD, 2017), which aim to capture all transactions as the denominator.[7] Exhibit 2 shows the total number of home sales from HUD and the number of households that take out a first-lien purchase mortgage in a given year and did not have one in the previous 3 years, the CCP-based measure of first-time homebuyers.[8]

Given that the CCP data series starts in 1999, the measure of first-time homebuyers, with a 3-year lag, begins in 2002 and goes until 2015. The number of first-time homeowners is estimated to be more than 3 million each year during the period 2002 to 2005, peaking at almost 3.5 million in

[5] Equifax has provided this dataset to the Federal Reserve System since 2010 (Lee and Van der Klaauw, 2010). A drawback of this dataset is that it is not available to the public.

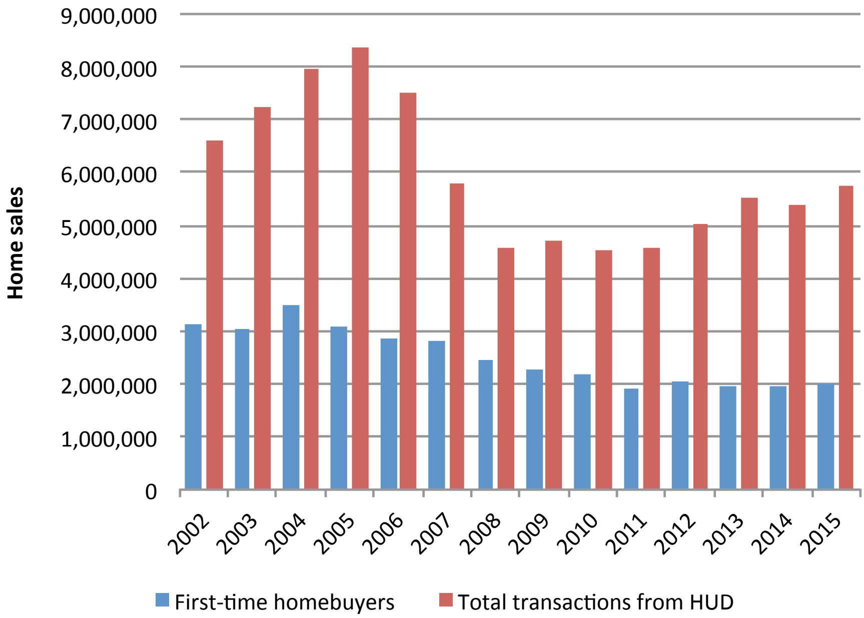
[6] Gyourko, Lee, and Tracy (2015) also used this method.

[7] We use HUD data for the denominator due to the difficulty of identifying owner-occupied home purchase mortgages in Equifax. This approach is limited due to the potential biases and noise introduced by relying on two different sources for numerator and denominator. However, it should capture the universe of home purchases in a given year.

[8] The total number of first-time homebuyers is very sensitive to various sample construction methods in the CCP; however, the trend of declining first-time homebuyers is robust across multiple possible definitions. Appendix A provides details and assumptions of the steps followed to identify household members in the CCP and limits associated with the CCP household definition.

Exhibit 2

Total Number of Home Sales Versus First-Time Homebuyers (2002–2015)



HUD = U.S. Department of Housing and Urban Development.
Sources: Federal Reserve Bank of New York Equifax Consumer Credit Panel; HUD database

2004. It then declines to 1.9 million in 2011 and remains very stable around 2 million through 2015, which is well below the historical levels. As of 2015, the number of first-time homebuyers is estimated to be roughly one-third below the level experienced during the housing boom.[9]

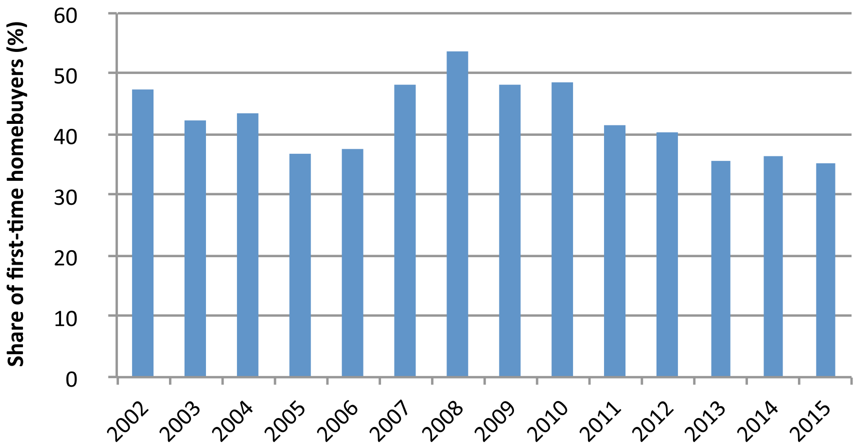
Using the HUD data to measure total home purchases, first-time homebuyers comprised about 40 percent of homebuyers between 2002 and 2004 (exhibit 3), a share consistent with the two existing measures.[10] The share decreases to 37 and 38 percent of all homebuyers in 2005 and 2006, respectively, directionally similar to the NAR series. That decline may reflect that, during the peak of the housing boom, many households were trading up and investors represented an increasing share of purchases (Haughwout et al., 2011). Subsequently, through the 2007-through-2010 downturn period, the first-time homebuyer share is elevated, likely reflecting the reduced mobility of existing homeowners (due to the drop in home prices) and a drop in first-time, all-cash buyers with a greater investment motive. Between 2010 and 2013, the share of first-time buyers declines sharply in this series and has remained low since then. The share of first-time homebuyers represents about 35 percent of all transactions in 2015.

[9] Given the natural exit from homeownership of households transitioning from owning to renting or passing away, and added exit due to foreclosures, the decline in the number of first-time homeowners resulted in no net change in the number of homeowners in the 2006-to-2016 period. As of 2016, the number of homeowner households was 75.0 million compared with 75.4 million in 2006 (U.S. Census Bureau, 2017).

[10] This share would be lower if we used never having had a mortgage instead of not having had one within the last 3 years.

Exhibit 3

Share of First-Time Homebuyers (2002–2015)

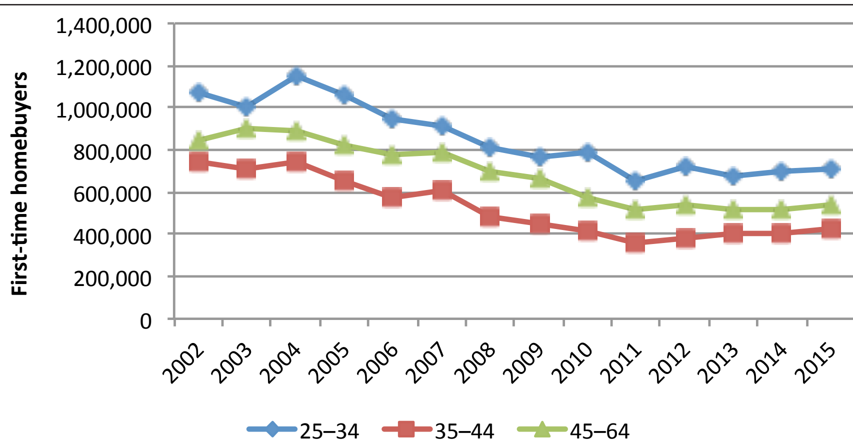


Sources: Federal Reserve Bank of New York Equifax Consumer Credit Panel for first-time homebuyers; U.S. Department of Housing and Urban Development for home sales

Further, we break down the total number of first-time homebuyers by age group. Across all age groups, we see significant declines in the number of first-time homebuyers from 2004 to 2011 (exhibit 4). After 2011, the number of first-time homebuyers stabilizes, for each of the age groups, at lower levels than the precrisis highs. Overall, from 2004 to 2015, the number of first-time homebuyers has declined roughly 40 percent for all three age groups. This suggests that the decline in first-time homebuyers is not simply due to younger people delaying home purchases by a few years; rather, purchase behavior seems to have shifted across all age groups.

Exhibit 4

Number of First-Time Homebuyers by Age Group (2002–2015)



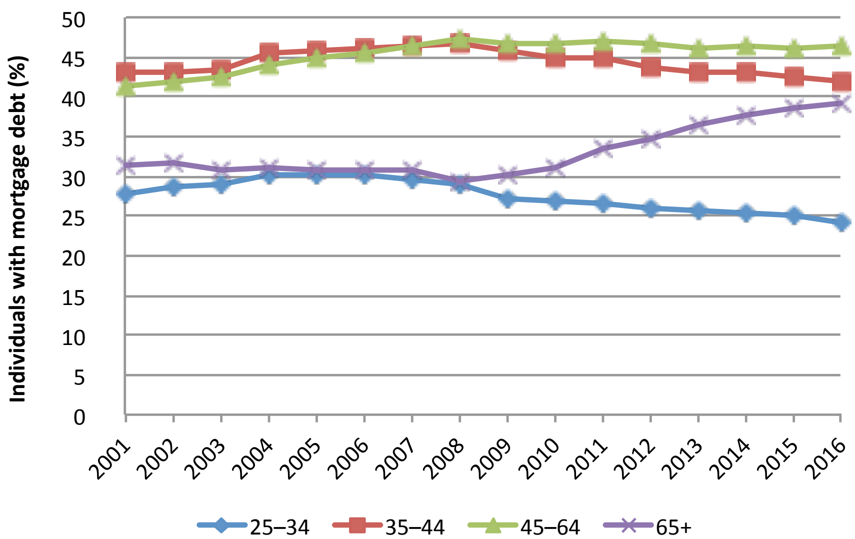
Source: Federal Reserve Bank of New York Equifax Consumer Credit Panel

We also estimate the share of individuals with a mortgage (as a ratio to all individuals with a credit record) by age groups. The CCP data show that it is younger people, under the age of 35, who have experienced the largest drop in the share of individuals with a mortgage (exhibit 5).[11]

The CCP allows us to examine the credit characteristics of mortgage debt holders. Exhibit 6 shows the share of first-time homebuyers by credit score level and the share of all households with a mortgage. It shows that the decline in the share of individuals with mortgage debt is most pronounced among lower-credit-score borrowers and that they represent a smaller share of first-time homebuyers in the postcrisis period. This finding is consistent with access to credit playing a role in the decrease in first-time homebuyers, as reported in Bhutta (2015). Another factor that might contribute to delayed access to homeownership is student debt (Elliott, Grinstein-Weiss, and Nam, 2013; Mezza et al., 2016).[12]

Exhibit 5

Share of Individuals With Mortgage Debt, First Liens Only, by Age Group (2001–2016)



Source: Federal Reserve Bank of New York Equifax Consumer Credit Panel

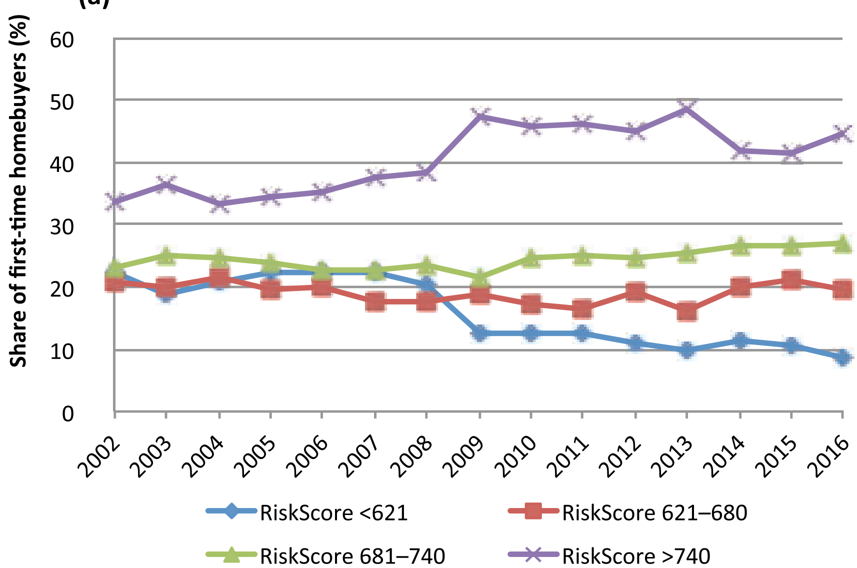
[11] These results on the decline in first-time homebuyers by age group imply that the drop in aggregate homeownership is not only the result of the forced transition from owning to renting by households experiencing foreclosure or short sales but also the result of fewer households, particularly younger households, gaining access to homeownership. These results are supported by findings reported in Bhutta (2015), who decomposed the entry and exit of mortgage debtors and found that the decrease in the volume of new entrants far outpaced the volume of exits.

[12] The role of student debt in postponing access to mortgages is consistent with findings that attribute the changes in the homeownership rate to the increased impact of credit constraints (Acolin et al., 2016a; 2016b).

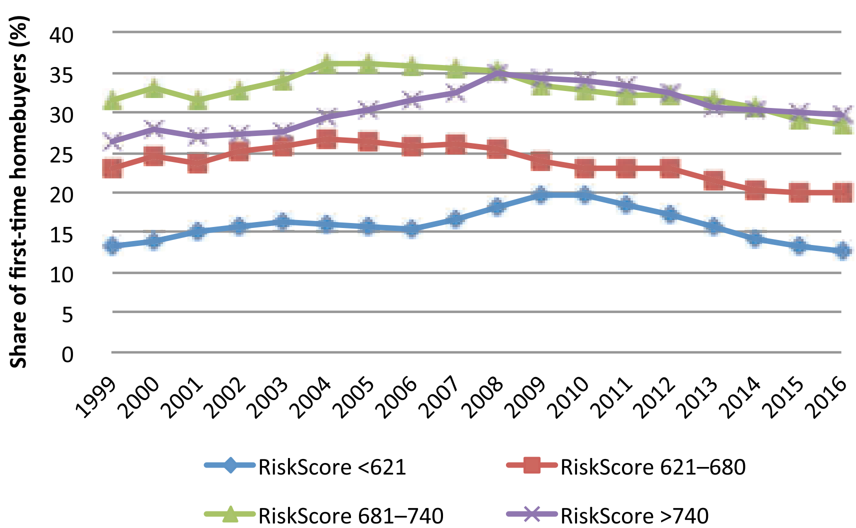
Exhibit 6

Share of First-Time Homebuyers by Credit Score Level (a) and Share of Individuals With a Mortgage by Credit Score Level (b)

(a)



(b)



Source: Federal Reserve Bank of New York Equifax Consumer Credit Panel

Conclusion

In this article, we present a new measure of first-time homebuyers as a share of all purchasers. Existing measures yield divergent assessments of this ratio. NAR provides a measure based on a survey, whereas AEI and UI provide measures based on administrative data and include only purchases with a mortgage that involved the GSEs or FHA. In this article, we use a new dataset to construct a time series of the share of first-time homebuyers. This series, based on the Federal Reserve Bank of New York Equifax CCP, shows a significant decline in the share. We also find a decline in the number of first-time homebuyers across all age groups relative to the early 2000s.

Appendix A: Data Steps

The Federal Reserve Bank of New York Equifax Consumer Credit Panel is a 5-percent sample of all individuals with at least one credit record. These individuals form the principal sample and are given an identification number (ID) that remains constant over time. In addition, in any quarter, a household ID is attributed to all credit records sharing the same address as individuals in the principal sample. Credit records for the members of that household are also available over time (until they move out of the Primary consumer's household).

We use the following steps to identify the number of first-time homebuyers defined as not having had a first lien mortgage in the previous 3 years and having one in that quarter—

- Extract all individuals in a given quarter and their household IDs.
- Drop duplicate household IDs so that each household has only 1 record.
- Draw a 1-percent sample of households.
- Match the household IDs from the household sample back to the individual IDs.
- Drop households with more than 10 records (likely to be multiunit addresses rather than real households). This sample is of individuals in the households used to determine the number of first-time homebuyers.
- Use the individual IDs to extract mortgage history for all individuals in the sample of households.
- Identify whether each individual had a mortgage in any of the previous 12 quarters. If an individual had no mortgage in any of these quarters and has one now, identify the individual as a first-time homebuyer, even if missing data during one or more quarters.
- If any member of the household is a new homebuyer and none of the household members had mortgages in the previous 3 years, identify the household as first-time homebuyer.
- Sum the number of first-time homebuyer households.
- Extrapolate the number of first-time homebuyer households identified from the sample to the entire population.

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Authors

Arthur Acolin is an assistant professor of real estate at the University of Washington.

Paul Calem is a vice president in the Supervision, Regulation and Credit Department at the Federal Reserve Bank of Philadelphia.

Julapa Jagtiani is a special advisor in the Supervision, Regulation and Credit Department at the Federal Reserve Bank of Philadelphia.

Susan Wachter is Albert Sussman Professor of Real Estate and professor of finance at The Wharton School of the University of Pennsylvania.

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Do It Yourself: Obtaining Updated Transit Stop and Route Shapefiles in Urban and Nonurban Areas

Seva Rodnyansky
University of Southern California

Abstract

Research that combines housing and transportation aims to jointly understand the elements of neighborhood accessibility, affordability, and sustainability. Access to high-quality public transit and nonmotorized transportation helps reduce emissions and transportation costs for all households, including those with lower incomes. Transit access also expands the range of community destinations and shopping opportunities for those without cars. However, researchers often struggle to obtain accurate, geo-coded data—especially in suburban and nonurban areas—on transit station locations, routes, and schedules. This article highlights a newer tool, the General Transit Feed Specification (GTFS) from Google, which provides an open source database of updated transit data. This free data source combines static and dynamic transit data and can be incorporated into analysis using geographic information system, or GIS, software. It also significantly eases cross-sectional, rural, and metropolitan-areawide analyses of housing using transportation as a key input. This article summarizes the GTFS data type, gives an overview of methods for using the data, explores current uses of the data, and suggests future applications.

Introduction

Accessibility to employment and amenities is a primary input to a household's choice of residential location. In the monocentric city model, households commute to jobs in the central business district and select housing locations by trading off the cost of commuting longer distances versus the higher cost of housing closer to the city center (Alonso, 1964; Brueckner, 1987). Although many U.S. metropolitan areas are less monocentric today than they were in the middle of the 20th century, many households still commute to downtowns or to local employment centers and must thus factor transportation into their location decision (Giuliano and Small, 1991; Redfearn, 2007). The same is true of other amenities households use—shopping, entertainment, educational, medical, and so on—which tend to cluster in particular locations, necessitating transportation.

Location accessibility depends on the transportation mode available and chosen. For example, a housing development near an interstate highway exit, but with no public transit, may have high accessibility for households with car access but low accessibility for those with no or low car access. However, if this highway is routinely congested, the traffic may lower the site's relative accessibility. If the same housing development had nearby bus access, its relative accessibility would still depend on the distance to the bus stop and on the frequency of bus service. Thus, while both the highway and the bus service may appear nominally accessible, in reality, traffic and transit service constraints may decrease the location's accessibility. Hence, when making residential location choices, households must optimize housing cost, job and amenity accessibility, mode choice, traffic, and transit service.

Researchers and policymakers who design and evaluate housing policies also need to take accessibility into account. Combined housing and transportation research aims to understand the combined elements of accessibility, affordability, and sustainability at both the household and neighborhood levels (Haas et al., 2013).

Measuring accessibility to account for transit service and traffic can be complex. Prior measures of location or neighborhood accessibility (for example, Alonso, 1964), used linear (Euclidean) distance, which gives only an approximation and is less suitable for cities with irregular topography or with grid street layouts, which includes many U.S. cities. More recent commercial Global Positioning System (or GPS)-based tools, such as Google Maps, take street network and congestion into account and have improved accessibility measurements for automobile, public transit, biking, and walking modes. Although Google Maps and similar tools work well for individuals, researchers and policymakers need data to be aggregable and analyzable over various time periods. For driving modes, this goal has been accomplished by using street network analyses in geographic information system (GIS) packages and by aggregating road sensor data, such as the Archived Data Management System (Giuliano, Chakrabarti, and Rhoads, 2016) in Los Angeles, California, but this method has helped enhance accessibility measurements for only automobiles, not other modes like public transit, walking, and biking.

Data on public transit stop location, service, and performance on an aggregate basis over multiple time periods are scant, limited to a few of the largest and most sophisticated transit operators in the United States, housed on multiple websites and in a variety of data types. A new data source, the General Transit Feed Specification (GTFS), has solved many of these issues simultaneously by providing a centralized database of current and historical transit stop locations, service times, and performance using the same file type. GTFS enables public transit accessibility measurements that were previously impossible or impractical. In a recent research project, which required obtaining the location of every bus stop in California, GTFS reduced data-gathering time from 3 months to 1 week and increased data completeness from 49 to 88 percent of counties (Bostic and Rodnyansky, 2016). The remainder of this article gives background and tips on using GTFS, showcases relevant research using GTFS, and provides ideas for future use in housing and neighborhood research.

GTFS Background

GTFS is an open-data tool connecting transit operators and users of transit data. GTFS is a unified standard file format for sharing transit route, stop, schedule, and performance data, interoperable among transit operators worldwide, regardless of size, language, or transit type.[1] The GTFS file format was developed through a partnership between TriMet, the transit operator in the Portland, Oregon metropolitan area, and engineers at Google, Inc. (McHugh, 2013). This initial project helped launch and integrate transit tracking and transit time measurement into Google Maps (McHugh, 2013). The public and institutional success of the Portland example encouraged other U.S. and international transit agencies to adopt the GTFS file format and provide their data to the public. Since the launch of the Portland project, data from at least 1,000 agencies worldwide have become available through GTFS. Moreover, an extension of GTFS called "GTFS-realtime" expands the available data to include real-time trip updates, service alerts, and vehicle positions, enabling more nuanced analyses.[2]

GTFS Do-It-Yourself

GTFS is a simple and accessible tool, by design. Researchers, policymakers, and others interested in transit data can download and perform analyses on GTFS data with tools as simple as spreadsheet software (for example, Microsoft Excel), text reader (for example, Windows Notepad), and GIS software (for example, Esri ArcGIS, PitneyBowes MapInfo, or open source QuantumGIS).

Each participating transit agency uploads as many as 13 files describing the various aspects of their transit operations. These files include stop locations and times, service frequencies, routes and route shapes, trips, fare attributes and rules, transfers, service calendars and off days, and agency and feed descriptions.[3] Those agencies participating in GTFS-realtime include additional files describing in-time vehicle positions, trip updates, and service alerts. Note that not all agencies choose to upload every file, and not all agencies update their files with every service change.[4] The files for each participating agency are downloadable in text, comma separated value, shapefile, or a combination of the three formats, depending on the agency and file type.

After downloading the data, users have several options in operationalizing it, depending on their purpose. At the simplest level, users can examine their data in a spreadsheet or a text reader, if they know the specific route or stop they seek. Most users, however, will want the view of all the stops and all the routes. To enable proper location of stops and routes on a map, GTFS data provide latitude and longitude coordinates. For agencies that provide GIS shapefiles, coordinates and projections will appear automatically once opened in GIS. For agencies that provide text files, users should import the text file into GIS, use the system's coordinate reader, and set a projection.[5] These

[1] https://developers.google.com/transit/gtfs/.

[2] https://developers.google.com/transit/gtfs-realtime/guides/feed-types.

[3] https://developers.google.com/transit/gtfs/examples/gtfs-feed.

[4] Some agencies update their GTFS data frequently. For example, the Sacramento Rapid Transit District has GTFS data posted from six time periods from 2013 through 2017 (SACRT, n.d.).

[5] Vance (2016) provides a handy tutorial for QGIS using the Cook County, Illinois Pace bus service. This tutorial readily generalizes to ArcGIS and other GIS software.

files can now be integrated with other geographic data. Alternatively, GTFS files can also be converted to a KML file for use with Google Earth.[6] To take advantage of the timetables and schedules provided via GTFS, users can plug GTFS into a network dataset for use with Esri ArcGIS Network Analyst, using a custom-written toolbox "Add GTFS to a Network Dataset" (Morang, n.d.).

The U.S. Department of Transportation (DOT)'s National Transit Map project, through the Bureau of Transportation Statistics, provides a GTFS-derived national map of all transit stops and all agencies whose data are represented (DOT, n.d.). A GIS shapefile of 0.5- and 0.25-mile buffers around fixed-route transit stops is also provided and may be especially useful for those studying transit-oriented development and accessibility at the national level.

For users looking for data from a specific transit agency, no single website provides all GTFS-participating agencies, due to the data's open-source nature. However, several sources provide overlapping lists of participating agencies and clickable links to download data directly or to the transit agency's webpage on which the data are hosted (exhibit 1). Housing and neighborhood policy researchers can use these sources to complement their analyses with realistic and detailed portrayals of transit accessibility.

To demonstrate an example, I set out to find and display all the bus stop locations in Fresno and Madera Counties in the San Joaquin Valley of California. Fresno County, with a population of 950,000, contains the Fresno metropolitan area, and Madera County, with a population of 150,000, contains the city of Madera. Fresno County has two main transit operators—Fresno County FAX and Clovis Transit—regularly operating 20 routes, and Madera County has one—Madera County Transit, with three routes. Using the GTFS Data Exchange listing, I sourced and downloaded the data from each county's transit feed;[7] both were already in shapefile format upon download. I imported both shapefiles into open-source QuantumGIS, in addition to layers showing county and city boundaries and a layer showing major roads. Exhibit 2 visualizes both counties' transit stops with dots demarcating stop locations. Researchers can readily replicate and extend such an analysis and visualization with the available GTFS data.

Exhibit 1

Sources To Find GTFS Data for Specific Transit Agencies

Source Name	Total Transit Agencies Listed	Website
TransitLand	2,090; about 1,000 have GTFS	https://transit.land/feed-registry/
GTFS Data Exchange	1,000	http://www.gtfs-data-exchange.com/agencies
Transitfeeds	550	http://transitfeeds.com/feeds
Transitwiki.org "Publicly accessible public transportation data"	401	https://www.transitwiki.org/TransitWiki/index.php/Publicly-accessible_public_transportation_data
Google Code Archive: googletransitdatafeed—PublicFeeds.wiki	256	https://code.google.com/archive/p/googletransitdatafeed/wikis/PublicFeeds.wiki
Trillium	150 or more	https://trilliumtransit.com/gtfs/our-work/

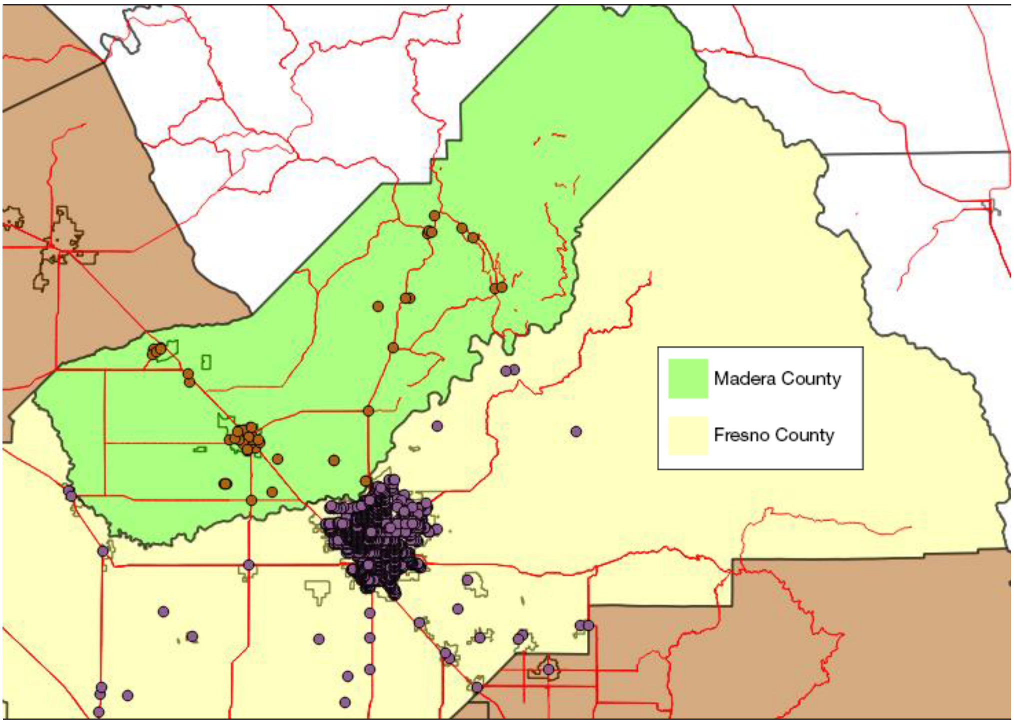
GTFS = General Transit Feed Specification.

[6] See Antrim (2015).

[7] Fresno County data feed: http://data.trilliumtransit.com/gtfs/fresnocounty-ca-us/; Madera County data feed: http://data.trilliumtransit.com/gtfs/madera-ca-us/.

Exhibit 2

Visualization of Bus Stop Locations in Fresno and Madera Counties Using GTFS Data



GTFS = General Transit Feed Specification.

Current Uses of GTFS

Current users of GTFS range widely from transit agencies, app and website developers, transit planners, researchers, and others. DOT's Federal Transit Administration reports that the "GTFS format is used by many transit agencies to communicate their schedules to online mapping programs and smartphone/tablet applications that travelers use to plan their transit trips" (DOT, 2016). GTFS.org, a website supported by the nonprofit Rocky Mountain Institute, reports six major applications of GTFS: (1) trip planning and maps, (2) timetable creation, (3) accessibility for the disabled, (4) planning and analysis, (5) real-time transit information, and (6) public information displays (GTFS.org, n.d.).

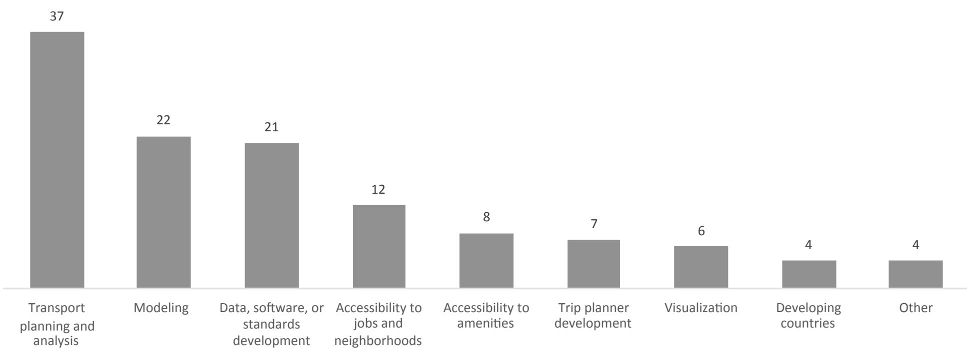
The previously mentioned categories intuitively make sense but do not give an understanding of the use of GTFS in research. To assess the depth and breadth of GTFS penetration into research, I conducted a literature scan of GTFS-related scholarly publications, agency reports, and unpublished working papers and theses. I used the GoogleScholar and Google search engines with a timeline from 2005[8] to the present and a targeted list of search terms: GTFS, General Transit Feed Specification, Google Transit Feed Specification, GTFS and geography, GTFS and planning, GTFS

[8] The earliest development of GTFS by TriMet and Google was in 2005.

and urban, GTFS and rural, and GTFS and transit. The literature scan yielded 121 relevant results, most from 2013 through 2017, published in a variety of journals and fields. Studies were categorized based on their main research angle. More than one-half of the research was specific to the transportation field: transportation planning and analyses, improved transportation modeling, and developing trip planners (exhibit 3). Another 21 studies focused on software, standards, or data development stemming from GTFS, and 6 studies used GTFS for visualization. Finally, less than 20 percent of studies focused on accessibility to jobs, neighborhoods, or amenities—our topic of interest. These accessibility-related studies are most relevant for housing, planning, and neighborhood researchers and set a precedent for incorporating GTFS in such research.

Exhibit 3

Counts of GTFS-Related Research by Category



GTFS = General Transit Feed Specification.

Accessibility to Amenities

Select scholars have used GTFS data to more accurately measure public transit accessibility to amenities including healthcare facilities, grocery stores, schools, and retail. Given the reliance of many low-income households on public transit, these studies help inform policymakers on the disparities in amenity access between driving and transit modes. A 2015 study in Melbourne, Australia, was among the first to demonstrate the potential of GTFS to measure amenity access. Rocha et al. (2015) assessed the transit accessibility of emergency dental care by differentiating patients by socioeconomic status and proximity to high-frequency bus stops. Using GTFS, they found that households living in areas with no high-frequency bus stops were no less likely to seek emergency dental care than those living in areas with high-frequency bus stops. A study of shopping amenity access in Montgomery and Prince George's Counties in Maryland found, using GTFS data, store locations to be "strongly influenced by access to transportation facilities, especially bus and light rail transit stops" (Ma, Knapp, and Knapp, 2014: 2). Mechaber (2015) found that access to selective enrollment and magnet high schools in Chicago was inequitable, when taking into account GTFS-derived public transit travel times, because it takes longer to get to these schools by transit than by car. School locations were found to be inequitable with respect to minority status and income, because lower-income and minority pupils both lived farther away from the schools and were more reliant on transit to get to school.

Another set of studies compared spatiotemporal accessibility to grocery stores via public transit versus driving, using GTFS data from the Cincinnati, Ohio metropolitan area. They found that food deserts for transit-dependent households change shape depending on the time of day and day of the week, due to the transit schedule, while car-dependent households have a more fixed food desert definition (Farber, Morang, and Widener, 2014). Further, Widener et al. (2015) found that many Cincinnati-area residents have improved accessibility to supermarkets if they access them on their return trip from work rather than departing from home. Widener (2017) extended this research to show that transit-dependent households have poorer spatial access to healthy food, as measured by the cumulative access to multiple grocery stores, and that transportation to obtain the healthy food is more costly using transit compared with driving modes. A followup study in the greater Toronto, Canada area finds that grocery store access in late nights and early mornings is lower for transit users than for car users (Widener et al., 2017). This finding is relevant because many lower-wage service employees have unconventional schedules and lower access to cars, necessitating transit accessibility to grocery stores at very late or very early hours. These studies barely scratch the surface of what is possible with GTFS in measuring amenity accessibility.

Accessibility to Jobs and Neighborhoods

A limited number of studies have used GTFS to study neighborhood and employment accessibility—major topics of interest for housing, planning, and neighborhood researchers. A cross-sectional analysis by Owen and Levinson (2014) used GTFS to rank 46 of the top 50 most populous U.S. metropolitan areas by average transit accessibility to jobs. They provided a realistic weighted average transit-travel time between residences and employment areas, from 7:00 to 9:00 a.m., including getting to and from public transit and any necessary transfer. New York, New York; San Francisco and Los Angeles, California; Washington, D.C.; and Chicago, Illinois, top the list in job accessibility by transit (Owen and Levinson, 2014). A San Francisco Bay Area simulation analysis found that the region has high job accessibility by walking and by transit, but disparities existed between census blocks in poverty and not in poverty (Blanchard and Waddell, 2017). Ma and Knaap (2014) demonstrated the use of GTFS and Open Street Map, another open data source, on neighborhood-level job accessibility for neighborhoods surrounding the proposed Purple transit line in the Maryland suburbs of Washington, D.C. Their model showed outcomes for two planned stations. Langley Park, a neighborhood with a high proportion of low-skilled workers, would see an 80-percent increase in low-skilled jobs accessible by transit when the transit line opens. For Bethesda, a regional employment center, 70,000 more employees would be within 1 hour on public transit once the line opens.

Several studies addressed transit equity at the neighborhood level by assessing differences in transit supply versus transit demand. Jiao and Dillivan (2013) found "transit deserts"—neighborhoods that lack adequate transit service but maintain high proportions of transit-dependent populations—near the historic downtowns and isolated rural areas of the Charlotte, North Carolina; Chicago; Cincinnati; and Portland metropolitan areas. Kahrobaei (2015) found that low-income neighborhoods with a high proportion of commuting workers have low bus frequency during the morning rush, necessitating a high degree of car ownership. Others proposed and evaluated a Gini coefficient-like measure of transit supply distribution equity, tested using GTFS data (Bertolaccini, 2013; Bertolaccini and Lownes, 2013).

Research relating housing to transit accessibility using GTFS has been limited. Zhong et al. (2017) harnessed GTFS to derive a model for optimally siting affordable housing to maximize residents' access to public transit and reduce geographic clustering of affordable housing, subject to land acquisition and construction budget constraints. Tested for Tempe, Arizona, the model "could provide insightful spatial decision support to affordable-housing providers or tax-credit administrators, facilitating the design of flexible strategies that address multiple social goals" (Zhong et al., 2017: 1). A study of California low-income housing tax credit affordable housing sites showed no statistical difference in transit accessibility between allocated (9-percent) and tax-exempt bond-derived (4-percent) tax-credit projects or between funded and nonfunded 9-percent tax-credit projects (Bostic and Rodnyansky, 2016). More research relating housing and transit accessibility is needed for both affordable and market-rate housing, and GTFS makes such research more attainable.

Conclusion

Transit accessibility is an important topic for housing researchers and policymakers at the national, regional, and local levels. GTFS data improve the geographic coverage, depth, and accuracy of measuring transit accessibility. Researchers and practitioners can use GTFS in a do-it-yourself manner, which was previously unavailable, to include better measures of transit accessibility into their analyses. These better measures are especially needed in housing-related research, which is underrepresented in its use of GTFS.

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Author

Seva Rodnyansky is a Ph.D. candidate in urban planning and development at the University of Southern California, Sol Price School of Public Policy.

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SpAM

SpAM (Spatial Analysis and Methods) presents short articles on the use of spatial statistical techniques for housing or urban development research. Through this department of Cityscape, *the Office of Policy Development and Research introduces readers to the use of emerging spatial data analysis methods or techniques for measuring geographic relationships in research data. Researchers increasingly use these new techniques to enhance their understanding of urban patterns but often do not have access to short demonstration articles for applied guidance. If you have an idea for an article of no more than 3,000 words presenting an applied spatial data analysis method or technique, please send a one-paragraph abstract to rwilson@umbc.edu for review.*

Calculating Varying Scales of Clustering Among Locations

Ron Wilson
University of Maryland, Baltimore County

Alexander Din
Maryland Department of Housing and Community Development

The views expressed in this article are those of the authors and do not represent the official positions or policies of the State of Maryland.

Abstract

The Nearest Neighbor Index (NNI) is a spatial statistic that detects geographical patterns of clustered or dispersed event locations. Unless the locations are randomly distributed, the distances of either clustered or dispersed nearest neighbors form a skewed distribution that biases the average nearest neighbor distance used in calculating the NNI. If the clustering or dispersion of locations is moderate to extreme, the NNI can be inaccurate if the skew is substantial. Using Housing Choice Voucher program residential locations, we demonstrate in this article the method to derive an NNI based on a median and two quartiles that more accurately represents the midpoint of a set of nearest neighbor distances. We also demonstrate how to use these alternative point estimates to gauge multiple scales of clustering from different positions across the nearest neighbor distance distribution. Finally, we discuss how to use the average and standard deviation distances from the calculation of each NNI to more comprehensively gauge the scale of the geographic patterns. We also include a Python program that creates a randomized set of locations to calculate statistical significance for the median and quartile NNIs.

Voucher Residence Locations and Clustering

The Housing Choice Voucher (HCV) program enables low-income families to relocate to neighborhoods of their choice (HUD, 2012). A key objective of the HCV program is the deconcentration of families to select better neighborhoods in which to live and improve their lives (Winnick, 1995). A common concern about this relocation freedom is that HCV program participants will reconcentrate in the destination neighborhoods. Research shows that, after receiving assistance, voucher holders often relocate to neighborhoods similar to those in which they previously lived (Freeman and Botien, 2002; Huartung and Henig, 1997; McClure, 2010; McClure, Schwartz, and Taghavi, 2014; Metzger, 2014; Park, 2013; Pendall, 2000; Owens, 2017; Reece et al., 2010; Varady, Walker, and Wang, 2001; Varady et al., 2010; Wang, Larsen, and Ray, 2017; Wang, Varady, and Wang, 2008; Wilson, 2013; Zielenbach, 2015). Relocating to similar neighborhoods subverts the objective of the program, and voucher holders are little better off than they previously were. Therefore, housing authorities need to measure the degree of clustering or dispersion of HCV program participant residences to determine if the objective of deconcentration is being met.

A common measure of location concentration or dispersion is a nearest neighbor analysis using the calculation of the Nearest Neighbor Index (NNI). The NNI is a common global measure of clustering or dispersion, but its accuracy is vulnerable because it is based on an average. Event locations are typically concentrated, which skews the nearest distance distribution positive, because most of the locations are within close proximity to each other. The NNI will be based on a skewed distribution of distances. This problem is especially acute with voucher holders, who often live very close together because the geography of affordable housing stock puts them in the same multifamily building or neighborhood. Another limitation is that these neighborhoods vary in size, meaning that the scale of residential clustering will vary across a geography, from close-quarter environments of multifamily housing, to dense townhomes, to single-family homes with land. This change in scale is not something the standard NNI can take into account, because it is a point estimate for one position on the nearest distance distribution.

As such, a more reliable and multiscale measure must be used to determine the degree of HCV residence concentration. An inaccurate measure can report that voucher holders may be more or less concentrated than they really are, which would have adverse resource ramifications. For example, if the results show that voucher holders are more clustered than they are, then it may appear as though the program is not working and some other solution should be sought. Conversely, if the results show that voucher holders are more dispersed than they are, then it may appear the program is working and that it requires fewer resources.

We demonstrate a method to conduct a more robust nearest neighbor analysis by calculating median and quartile NNIs to overcome the limitations of the common NNI. The medians and quartiles are less susceptible than an average to outliers, and they provide more visibility into concentration patters at multiple spatial scales.

Nearest Neighbor Index

The NNI is an ordinal statistic that reports the existence and degree of clustering or dispersion of locations (geometric points). The NNI is a member of a family of cluster measuring statistics, which includes the more common Moran's *I* and Getis-Ord statistics. The NNI, however, is considered a distance analysis statistic because it strictly measures proximity between locations. In contrast, the Moran's *I* and Getis-Ord *G* statistics can measure proximity between locations not only with distances, but also with buffers around any location or adjacency when data are in areal form (polygon geographies).

Two key assumptions of any analysis involving nearest neighbors are that the sample locations are (1) all included within a finite geography and (2) unimpeded in occurring anywhere in that finite geography (Ebdon, 1985). Empirically, neither assumption ever holds for human or physical events. Related event locations often exist outside of a geography but are unavailable for measurement, leading to missing data that impact the calculation of the NNI statistic. More importantly, it is unrealistic that locations can occur anywhere unimpeded across a geography because other spatial processes either facilitate or prevent locations from occurring anywhere. Nevertheless, these two assumptions are necessary for testing if locations exhibit a clustering or dispersing pattern in order to provide a counterfactual geographic distribution of locations for comparison.[1]

To calculate the NNI, all nearest neighbor distances are summarized into an average. That summarization implies that a distribution of distances exists that can provide more point estimates about those minimum distances. For example, the standard deviation and percentiles can be used to determine patterns at several geographic scales beyond the average. Those estimates can be used as parameter specifications in identifying clusters, such as in kernel density estimation, Knox Test, SatScan, or the local Moran's *I* and Getis-Ord *G*. A key aspect of cluster analysis is determining the distance at which locations are no longer related to each other, that is, the distance at which spatial dependence between the locations ceases. Lacking any theoretical reason or empirical evidence to select that expected distance leaves one to guess what that distance may be. With average, standard deviation, and percentile nearest neighbor distances, the data can be a guide to setting an expected clustering distance.

Calculating the NNI starts with a measurement of the distance between each location to the nearest location. The minimum distance between each location and it nearest neighbor is first summed and divided by the total number of locations in the geography to derive an average minimum distance. The average minimum distance is—

$$\bar{d}(NN) = \frac{\sum_{i=1}^{N} Min(d_{ij})}{N} \quad , \tag{1}$$

[1] Caution should be exercised in regards to comparing results from any nearest neighbor analysis to which any comparison of techniques should be done in the same study whether (1) between two different location types or (2) the same location type distributions across time. Comparing analyses between any two geographies confronts the problem that is the root of spatial statistics; that is, having to use randomization as the comparison distribution for significance of a clustering or dispersion pattern. The main problem is that each geography is unique in size and shape and will impact the distribution of event locations that directly affect the statistical results for each geography. Another consideration is that two entirely different distributions can have the same result.

where d is the minimum (*Min*) distance between location i and the closest location j, N is the total number of event locations, and $\bar{d}(NN)$ is the average minimum distance from measuring all nearest neighbors to each location. The average minimum distance is used in comparison—as the numerator—with a random (expected) distance to determine if the locations exhibit an overall pattern of clustering, dispersion, or random distribution.

The random distance represents an expected minimum nearest neighbor distance from which the locations are uninfluenced in that geography by social, economic, physical, or contextual activity—that is, the random locations from a distribution under complete spatial randomness (Cressie, 2015).[2]

The NNI, then, is the observed average minimum distance divided by the expected (random) average minimum distance to produce a relative ratio that is interpreted as an index along a clustering-to-dispersion continuum.

$$NNI = \frac{Observed\ \bar{d}(NN)}{Expected\ \bar{d}(NN)} \quad (2)$$

The NNI is interpreted in relation to a value of 1. Values around 1 indicate the observed distribution is random. Values less than 1 indicate clustering, with values closer to the floor of 0 indicating extreme clustering. An index of 0.0 means all the locations are in exactly the same place. Values greater than 1 indicate dispersion,[3,4] with values closer to the ceiling of 2.149 indicating extreme dispersion.[5] An index of 2.149 means that all the locations are exactly equidistant from each other in a systematic pattern. Exhibit 1 shows the relationship between NNI values and their corresponding patterns along the continuum from 0 to 2.149.

Three limitations hinder the NNI statistic from being more robust. The first is that the NNI is a global statistic; it cannot report where any local pattern of clustering or dispersion is in the geography, only that one of the patterns exists within.

The second is that the index is an average, subject to outliers pulling the observed mean away from its true location in the distribution. Outliers are typically present in location data because most social, economic, physical, or other processes produce clustered locations, with dispersed or random patterns seldom occurring. With a nearest neighbor analysis, a high frequency of short distances is produced with a small number of longer distances that skew the distribution positive.

The third limitation, which is related to the first, is that the average distance is only a single-point estimate for a set of nearest neighbor distances. Single-point estimates give only a partial insight

[2] See appendix A for details on the mechanics of calculating the NNI expected distance.

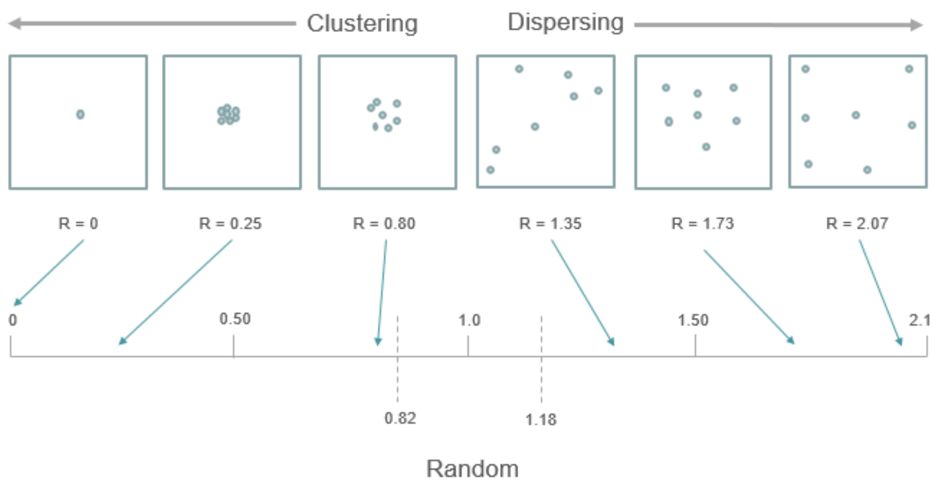
[3] Another way to think about the NNI is that the range of values reflects a progression from absolutely clustered (0, with all points in exactly the same location) to evenly dispersed (2.15, with all points maximally spaced from each other). This approach is useful when comparing indices to determine if one pattern is more or less clustered or dispersed than another pattern.

[4] The NNI can also be interpreted as a percentage more or less than the random distribution, because it is a ratio. For example, an NNI of 0.55 shows the observed nearest neighbor distances are 45 percent closer (1 – NNI = %) than the distances in the random distribution. An NNI of 1.67 shows the observed nearest neighbor distances are 67 percent farther (NNI – 1 = %) than the random distribution distances.

[5] The value 2.149 is the empirical ceiling of the NNI. Theoretically, a value could be higher, but none has been observed in previous research.

Exhibit 1

Range and Patterns of the Nearest Neighbor Index



R = ratio (between observed and expected).

into the spatial relationships between locations when varying scales of spatial relationships are likely in the geographic distribution. That is, different scales of clustering will likely exist across the geography due to variation in the structure of the environment. In this instance, neighborhoods where voucher holders live vary in scale, ranging from multifamily buildings, to dense inner-city blocks, to more spread out suburban, small town, or rural properties.

Nearest Neighbor Index Medians and Quartiles as Indicators of Multiple Spatial Pattern Scales

Most software packages that include the standard NNI technique report only the average nearest neighbor distance, which only allows for the assessment of geographic patterns at only one scale, the average distance between locations. Unless the standard deviation distance is also reported, any pattern variation at distances greater or less than the average is undetectable. However, even if the standard deviation distance is reported, highly clustered locations will have a skewed nearest neighbor distance distribution, and the one-standard deviation distance below the average will likely be less than 0 and useless for identifying any scale changes below the average. Calculating median and quartile distances, however, can reveal differing pattern scales at three locations along the distance distribution. The first scale is that of the densest locations, represented by the first 25 percent of nearest neighbor distances. The second scale is the moderately proximal locations, represented by one-half (50 percent) of the distances at the median. Finally, the third quartile NNI would be the more dispersed distances, represented by 75 percent of all locations, or the top 25 percent furthest distances.

If the scales were all similar, then the NNI would be the nearly the same for each of the point estimates, and the intervals between each index would also be similar. This result will suggest a distance distribution that is normal in shape with a high kurtosis. If the scales are different, then the NNIs will be far apart and the distribution of distances will be spread out, with the intervals between each index varying. This variation in intervals would indicate a distance distribution that is not normal in shape.

Lastly, the median and quartile NNIs can also measure the way in which the differing scales of clusters impact the average. Comparing the observed average with the median and quartiles reveals how far off the average is from the actual mean. Not only can the average distance be compared with the median to gauge how much they differ, but the average can also be compared with the quartiles to determine how far off the average is from different positions in the distance distribution. If the median and quartile NNIs are all below the average NNI, it indicates that the distribution is heavily skewed positive. If the first quartile and median NNIs are lower than the average, but the third quartile NNI is greater, it would indicate that distribution of distances is not too skewed, and the average distance may be acceptable in calculating the NNI, particularly if the average is closer to median NNI.

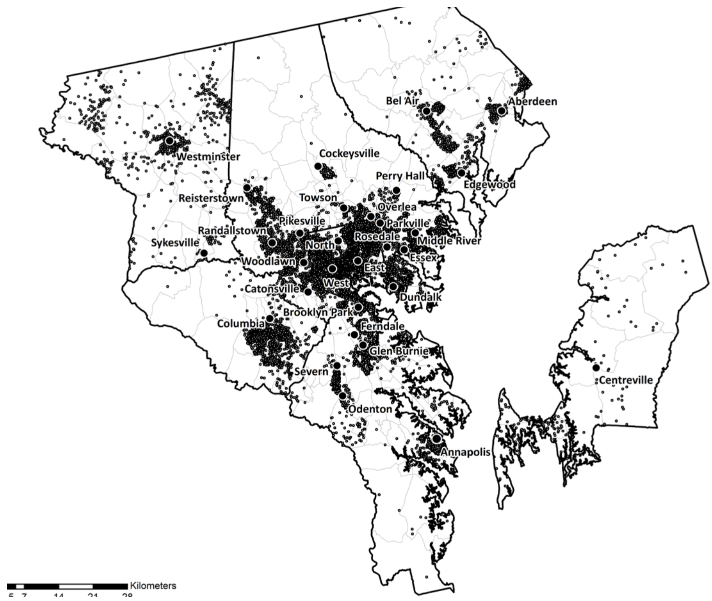
Data

The data used in this example are the counts of 2016 HCV program participants by census tract in the Baltimore-Columbia-Towson, MD Core Based Statistical Area (hereafter, Baltimore CBSA). The data were acquired via the U.S. Department Housing and Urban Development (HUD) enterprise geographic information systems (GIS) storefront. The total number of participant locations is 23,081. Because HUD does not provide program participant locations, we simulated the locations in a two-stage process to create residential locations based on where people actually live, with several being at the same location to emulate residents in the same apartment complex (exhibit 2).

First, the counts of program participants were divided according to the proportion of residents within each block group contained in each census tract. Second, a set of randomly distributed locations was created within each block group to simulate the locations based on known residential patterns. Some of these randomized locations were situated to be in the same coordinates to emulate voucher holders living in apartments or other multiunit residences. This two-stage process allows for a reasonable approximation of where HCV program participants live and reduces the risk of placing them in areas where populations do not reside (for example, forested portions, lakes, parks areas, and industrial sites).

Exhibit 2

Simulated Housing Choice Voucher Program Participant Locations Across the Baltimore CBSA



Baltimore CBSA = Baltimore-Columbia-Towson, MD Core Based Statistical Area.

Calculating the Nearest Neighbor Index Based on the Average Nearest Neighbor Distances

We first conducted a basic nearest neighbor analysis in CrimeStat IV to create the statistics for the NNI on the voucher holder locations in the Baltimore CBSA.[6] Exhibit 3 shows the results.

The results show the HCV program participant locations are moderately clustered, with an NNI of 0.58. This NNI value suggests that voucher holders are not too concentrated. An average distance of about 159 meters and standard deviation distance of about 835 meters suggest that voucher holders are quite spread out at a scale of several neighborhoods—about one-half mile. A standard deviation distance of about five times greater than the mean raises the concern that the NNI may be adversely affected from a skewed distribution of nearest neighbor distances. With geo-processing, we created a variable of nearest neighbor distances and examined the distribution to assess the accuracy of the reported NNI.

[6] We used CrimeStat IV because other GIS programs produce only a minimal listing of statistics, whereas CrimeStat IV provides much more valuable information that allows for more insight into the distance distribution. The nearest neighbor distance is typically all that is reported in most other GIS or spatial statistics programs, leaving the inability to complexly assess the scale of the clustering. With CrimeStat IV reporting the nearest neighbor standard deviation distance, the scale of clustering can be assessed, because it shows how far the locations are spread around the average distance. The standard deviation distances can be used in clustering routines to visualize the concentration of locations, and the distance can be used to gauge the number of blocks or neighborhoods the voucher holders actually cover.

Exhibit 3

Nearest Neighbor Statistics and Diagnostics

Descriptors of Nearest Neighbor Distances	Statistic/Diagnostic
Sample size	23,081
Measurement type	Direct
Mean nearest neighbor distance	158.60 meters
Standard deviation of nearest neighbor distance	834.76 meters
Minimum distance	0.00 meters
Maximum distance	438,731.80 meters
Area of geography (based on user input)	6,819,093,973.49 square meters
Mean random distance	271.77 meters
Mean dispersed distance	584.06 meters
Nearest neighbor index	0.5836
Standard error of random distance	0.94 meters
Test statistic (Z)	– 121.0332
p-value (one tail)	0.0001
p-value (two tail)	0.0001

Using the Near tool in ArcGIS, we calculated the distances of each location and its nearest neighbor and added them as a variable to the HCV location layer. The distance distribution showed an extraordinarily positive skew, with a skewness statistic of 14.65—a value far above the 0.50 threshold for skewness. Our analysis showed the NNI based on the average was very inaccurate and that deriving a median and quartile NNIs would prove worthwhile to improve our assessment of voucher holder concentration.

Calculating Median and Quartile NNIs

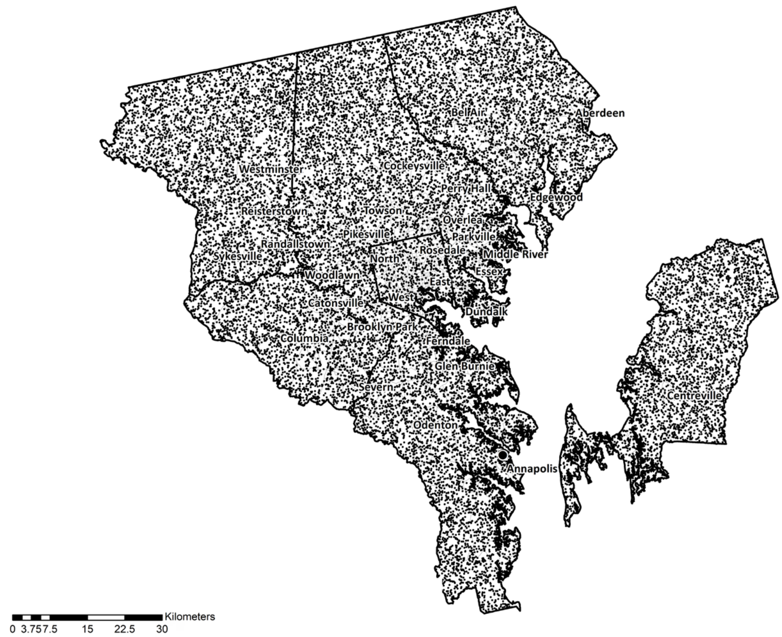
To create median and quartile NNIs, we first randomized 23,081 locations with 999 permutation trials within the Baltimore CBSA to create an expected distribution.[7] Randomizing the locations repeatedly is known as *bootstrapping* and builds an expected distribution against which to compare the observed statistics. The expected distributions represent the distances between locations if no social, physical, economic, or contextual process was influencing their placement. Bootstrapping produces a distribution from which a mean and standard error can be sampled for any point estimate, in this instance quartiles and the median. The mean of any point estimate from the 999 trials becomes the expected value against which to compare the observed statistics, with the standard error used to determine statistical significance of the observed quartile and the median NNIs.

Exhibit 4 shows an example geographic distribution from one permutation trail, in which HCV residences would be under complete spatial randomness with each voucher holder having equal

[7] Appendix B contains the Python code that randomizes the data set of 999 trials, including the output of the descriptive statistics for each trial.

Exhibit 4

Example of Random Permuted Voucher Locations Across the Baltimore CBSA



Baltimore CBSA = Baltimore-Columbia-Towson, MD Core Based Statistical Area.

probability of residing anywhere in the Baltimore CBSA.[8] We then repeated the geo-processing of nearest neighbor distances with the Near tool to create the random distribution of the 999 permutation trials and visualize the difference with the observed voucher holder nearest neighbor distances. The random distribution has an approximately normal shape, with a skewness value of 0.71.[9]

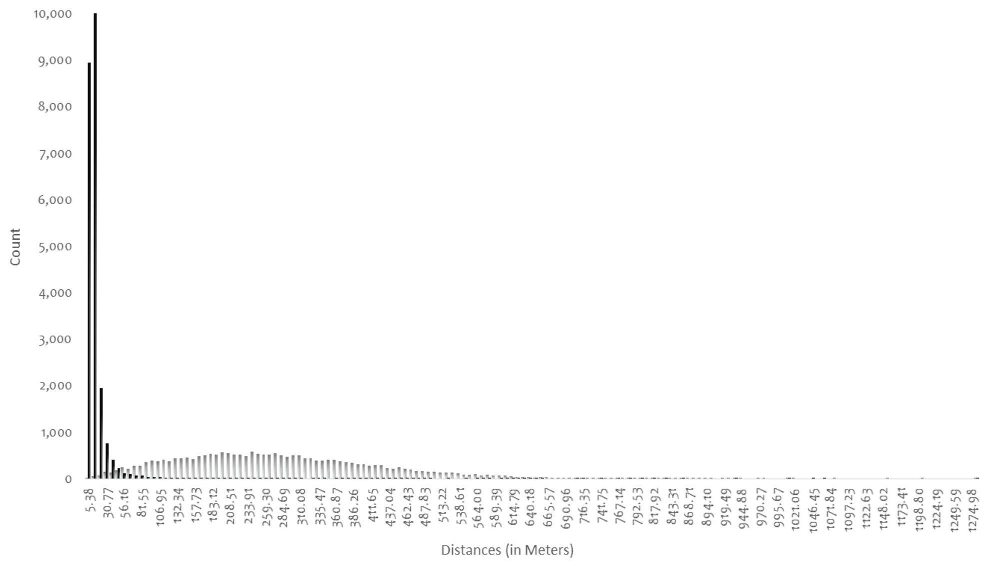
Exhibit 5 shows both the observed and randomized frequency nearest neighbor distance distributions for comparison.

[8] To make a more reasonable random distribution, the randomization process could be restricted to only geographies where voucher holders could live. The use of census tracts or block groups that show residential populations would comprise the area within which the randomization process would be distributed. The use of these geographies would give a more accurate expected average distance and standard error with which to compare the observed average and more precise NNI. Having the ability to randomize in a GIS allows for creating more realistic randomization processes. One of the fallacies of the randomization process under complete spatial randomness is that a location has equal probability of being anywhere in a geography, because nothing should prevent it from being anywhere. That may be likely for a physical process, but not for human settlement patterns. Only so many places exist in which voucher holders have an equal likelihood of residing, which would be places where affordable housing options are available, even if they are not likely to be housing options voucher holders can afford. However, that is where complete spatial randomness matters. If nothing prevents the voucher holders from residing in any housing unit, then randomizing across those units is more reasonable, because the voucher holders are not going to live where no housing exists at all. Therefore, the comparison is between the observed and the random places where a person could actually live. To be even more reasonable, only a certain percentage of housing units in a tract keeps the randomization process from locating a random location in just the areas with few housing units.

[9] Even a random distribution will produce some locations that are far apart, skewing the otherwise normal distribution positive.

Exhibit 5

Observed Versus Random Distances Between Nearest Neighbor Locations



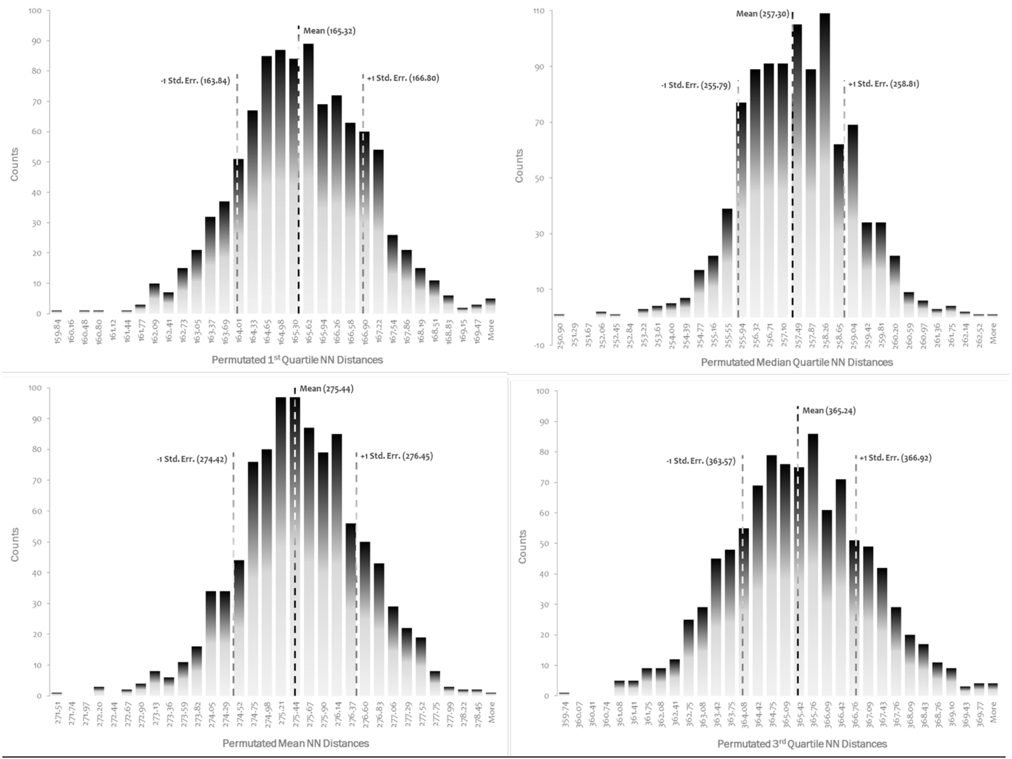
To ensure we calculated our 999 permutation trials correctly, we compared the random means and standard errors with results from the CrimeStat and ArcGIS formulas, noting that the differences were slight.[10] The comparison showed that our randomized trial results could be used to calculate the statistics for the median and quartile NNIs.

We then calculated the median and the quartile distances from the observed nearest neighbor distance distribution (exhibit 6), which were 0.00 meters for the first quartile (25th percentile), 16.20 meters for the median (50th percentile), and 118.82 meters for the third quartile (75th percentile). The average nearest neighbor distance showed to be greater than the third quartile of distances and nearly equivalent to the 82nd percentile of distances. Thus, the average distance used in the standard NNI calculation is representing a larger proximity scale—more spread out—between

[10] We compared the results with the NNI and z-score from CrimeStat and ArcGIS to compare the accuracy of our randomization process. The results between our randomization process and that of the software are similar enough, but not exact, because the two programs use a formula to estimate a standard error of a random distribution. CrimeStat and ArcGIS produced an average expected distance of 271.77 meters, and our randomization process produced 275.44 meters, a difference of 3.67 meters. CrimeStat produced a standard error of 0.97 meters, and ours was 1.01 meters, a difference of 0.04 meters. ArcGIS does not produce the standard error to allow for a comparison. We did a difference of means test comparing the CrimeStat formula results and the randomization results, which show the two are statistically different. This comparison shows that the formula is only an estimate that produces a result that is close enough but not as precise. Even though the formulas in CrimeStat and ArcGIS are reasonable approximations, they still are not as truly representative of a random distribution as permutation. Our results appear to back this conjecture, because the formulas produce a result that is close enough for practical purposes. Whether the average and standard errors from the formula or random process are used, the resulting NNIs will not be different enough to affect interpretation and will be identical if rounding to two decimal points to the right. Using the expected average nearest neighbor distance from CrimeStat and ArcGIS, the NNI is 0.584. The expected average distance from the randomization process is 0.576, a difference of 0.008. Nothing changes in the interpretation of the NNI, in that they both indicate a moderate level of clustering. Rounded to two decimal places to the right, as the NNI is often reported, both become 0.58, that is, identical.

Exhibit 6

Quartile, Median, and Mean Distance Distributions of Randomized Trials



NN = nearest neighbor. Std. Err. = standard error.

locations than ground truth. Although the NNI based on the average shows that voucher holders are clustered, for program evaluation purposes it shows them to be not nearly as concentrated as they really are.

With the statistics from the randomized trials, we calculated the average median and quartiles to create corresponding expected statistics for three NNIs, representing three different scales of location patterns (exhibit 7). The NNI for the first quartile is 0.00, median is 0.06, and the third quartile is 0.33. Each of these NNIs is less than the NNI based on the average, further showing that the NNI from the average distance is unreliable when a large number of geographic locations are in very close proximity.

To determine if our median and quartile NNIs were statistically significant, we used the standard errors of the median and quartiles from the 999 trials to calculate corresponding z-scores. The first quartile NNI of 0.00 has score of -111.63, the median NNI of 0.06 has a score of -159.34, and the third quartile NNI of 0.33 has a score of -146.91. All three NNIs are highly statistically significant. The intervals between the quartiles and the median are imbalanced, showing a change in clustering scales across the observed distance distribution. The difference between the first quartile and the median is 0.06, but the difference between the median and the third quartile is 0.27, showing that

Exhibit 7

Observed and Random HCVP Location Nearest Neighbor Index Statistics

	HCVP Location Distances (in Meters)			
	Observed	**Random**	**NNI**	***z*-score**
Average	158.60	275.44	0.576	– 115.22
Standard deviation	740.03	1.01		
1st quartile (25th percentile)	0.00	165.32	0.000	– 111.63
Standard error	—	1.48		
Median (50th percentile)	16.20	257.30	0.063	– 159.34
Standard error	—	1.51		
3rd quartile (75th percentile)	118.82	365.24	0.325	– 146.91
Standard error	—	1.68		

HCVP = Housing Choice Voucher participant. NNI = Nearest Neighbor Index.

the 50 percent of voucher holders above the median are about 4.5 times more dispersed than the 50 percent of voucher holders below the median. This finding indicates the voucher holders are, indeed, clustered at different scales. The use of median and quartile NNIs, therefore, can provide more information about geographic patterns in the data.

With the nearest neighbor distances created from geo-processing, the scale of the clusters can be assessed with the percentiles around the quartile and median to evaluate the varying scales of clustering among the locations. Exhibit 8 shows the NNI values at +10 percentiles around the quartiles and the median are used to reveal the scales of clustering by depicting the spread around each point estimate, including the interquartile range.[11]

The interquartile range shows the clustering of locations in the upper outer quartile to be about 6.3 times more dispersed than those in the inner quartile. This outcome indicates that locations with distances below the median are clustered in very close proximity. This finding reveals that 50 percent of voucher holders likely live on the same block, and the other 50 percent likely live in neighboring city blocks.

The percentile ranges provide more detail about the scale of clustering at each of the quartile and median distances. For the first quartile, the range of 0.00 meters between the 15th and 35th percentiles of nearest neighbor distances reports that the scale of clustering for 35 percent of voucher

Exhibit 8

Cluster Scales

Pertentile and Quartile Distance Ranges (in Meters)											
Ranges	*Min*	*15th Pctl*	*1st Qrtl*	*35th Pctl*	*40th Pctl*	*Median*	*60th Pctl*	*65th Pctl*	*1st Qrtl*	*85th Pctl*	*Max*
	0.00	0.00	0.00	0.00	4.05	16.20	39.26	57.55	118.82	187.34	23,444.30
Percentile			0.00			35.22			129.80		
Inter-quartile					*Lower* ←→ 16.20			*Upper* ←→ 102.62			

Max = maximum. Min = minimum. Pctl = percentile. Qrtl = quartile.

[11] Any percentile range can be used to examine the ranges around the quartile and median NNI.

holders is that of the same building or complex; the minimum is also 0.00 meters and indicates that two or more locations are in the exact same place. At the median, the range of nearest neighbor distances between the 40th and 60th percentile is 35.22 meters, indicating that 20 percent of voucher holders live on blocks with dense housing. Finally, between the 65th and 85th percentiles of nearest neighbor distances, 20 percent of voucher holders live within 129.80 meters of each other and are likely on contiguous blocks in a neighborhood. However, after the 85th percentile of nearest neighbor distances (187.3 meters), the voucher holders spread out substantially and are isolated from others given they are up to 23,444.30 meters away from the nearest voucher holder.

Summary and Extensions of the Interquartile NNIs

With highly clustered locations, we showed that the average nearest neighbor distance proves to be an inaccurate base to calculate the NNI. When using the statistic to help in assessing a program's performance, such as the HCV program, an alternative measurement must be used. The median and quartile NNIs not only provide more accurate results of the geographic pattern of clustering, but the statistics also provide more information about changes in clustering at differing geographic scales. In this example, the NNI based on the average distance inaccurately showed that voucher holders are only moderately concentrated, when they are actually far more clustered. Using the median and quartile NNIs, however, revealed that at least 25 percent of voucher holders were highly concentrated at the same location, with 26 to 75 percent likely living together in small neighborhoods. Given the nature of housing availability for HCV program participants, future analyses of the program will likely need to be analyzed with the median and quartile NNIs.

We offer a final thought about the geographies used to randomize when calculating any NNI. Typically, randomization is either implemented in the permutation process or is estimated with a formula that uses the area of the geography in which the locations occur. The use of the entire geography is based on the assumption that the locations can be equally likely to occur anywhere within that boundary. This assumption is unrealistic, because locations do not have equal probability of being anywhere, which is due to physical and human influences on a geography that restrict the occurrence of locations. We suggest running a second analysis limiting the geography to only areas in which the locations can actually occur. With voucher holders, these geographies would only be the areas in which rental housing is available. The boundary of the limited geography can be used in the permutation process with GIS as an alternative, by identifying all the areas that the analyzed locations can actually have the opportunity to occur.

Appendix A: Formula for Calculating an Expected Nearest Neighbor Distance

A random (expected) distance is generated by one of two randomization methods. The first method—which is rarely implemented in software—is to randomly distribute the same number of observed locations within an area that is either the size of their minimum bounding rectangle or within the study geography.[12,13] This randomization process is known as permutation, by which the observed data are used to generate a counterfactual (expected) distribution for what would occur in that unique geography. The second method uses a formula to approximate the Monte Carlo process, which is—

$$\bar{e}(NN) = 0.5\sqrt{A/N} \quad (3)$$

where $\bar{e}(NN)$ is the expected average distance, A is the total from the study geography in which the locations occur, and N is the total number of locations. The ratio produces a density, of which the square root is taken to produce a linearized value.[14] The constant 0.5 is multiplied to the linearized density ratio to rescale it and prevent the expected average distance from being larger than the study geography.

Appendix B: Python Code for Creating the Randomized Locations

```
# -*- coding: utf-8 -*-
"""
#This file creates random points in a given geography then takes statistics of distances of
the  ## nearest points.

## Author: Alex Din
"""
import arcpy
import csv
import numpy  as np
import os
from   random import randint
import time
##
start_time = time.time()
## this needs to be 1000 in order to get 999 iterations because of the range loop starts
at 1, not 0
iterations = 1000
## the number of random points to be created each iteration
pointsNum  = 23081
## the prjArea is the project area area geography which is the Baltimore CBSA in this
example
prjArea    = r"C:\Path\to\the\feature\class\for\the\project\geography"
## the csvName is the name of your output file, it MUST have '.csv' appended to the string
csvName    = "Baltimore_CBSA.csv"
## workspace is the geodatabase where functions will be performed
workspace  = r"C:\Path\to\the\working\geodatabase.gdb"
## dirspace is where your csv will be written, the directory must already exist prior to
running the script
dirspace   = r"C:\Path\to\the\working\directory"
## csvPath is the combination of the csvName and dirspace for outputing the final CSV
csvpath    = os.path.join(dirspace,csvName)
```

[12] Randomizing observed data is known as permutation.

[13] A minimum bounding rectangle is the outermost boundary of the furthest locations in each Cartesian plane orthogonal direction.

[14] The square root is taken to transform the two-dimensional density ratio into a one-dimensional distance so that it is geometrically comparable with the observed distance.

```
## the name of the random points
ptsName    = "samplepoints"
## the random number is used to export a random set of points for visualization purposes
randomNumb = randint(1, iterations)
## the work environments are set
arcpy.env.overwriteOutput = True
arcpy.env.workspace = workspace
os.chdir(dirspace)
## the print statement informs the user which
print "Iteration %s will be exported as a random copy for map purposes" %(randomNumb)
##
for number in range(1,iterations):
    print "Processing number %s" %(number)
    small_time = time.time()
    # create a set of random points within the project area
    try:
        arcpy.CreateRandomPoints_management(workspace, ptsName, prjArea, "", pointsNum,
"", "POINT", "")
    except Exception as e:
        print e
    # compute nearest neighbor distance
    try:
        nearValueList = []
        arcpy.Near_analysis(ptsName, ptsName, "", "NO_LOCATION", "")
        with arcpy.da.SearchCursor(ptsName,["NEAR_DIST"]) as cursor:
            for row in cursor:
                nearValueList.append(row[0])
        nearValueList.sort()
        # print the values in the IPython console to inspect while processing
        p25  = round(np.percentile(nearValueList, 25), 2)
        p50  = round(np.percentile(nearValueList, 50), 2)
        p75  = round(np.percentile(nearValueList, 75), 2)
        mean = round(np.mean(nearValueList), 2)
        std  = round(np.std(nearValueList), 2)
        var  = round(np.var(nearValueList,ddof=1), 2)
        maxx = round(np.max(nearValueList), 2)
        minn = round(np.min(nearValueList), 2)
        del cursor, row
    except Exception as e:
        print e
    # get the time it took to run just this one iteration
    small_time_end = time.time()
    small_elapse   = round((small_time_end - small_time),2)
    print "This iteration took %s seconds" %(small_elapse)
    # log the information to a CSV file
    # if the CSV does not yet exist, the CSV will be created with headers and append the
first iteration of data
    # else, if the CSV does exist, the information will be appended to a new row
    try:
        headRows = ["Number", "Seconds","25P", "Median", "75P", "Mean","STD", "Variance",
"Maximum","Minimum"]
        dataRows = [number,small_elapse,p25,p50,p75,mean,std,var,maxx,minn]
        if not os.path.exists(csvpath):
            with open(csvName, 'wb') as f:
                wtr = csv.writer(f, delimiter= ',')
                wtr.writerow(headRows)
                wtr.writerow(dataRows)
        else:
            with open(csvName, 'ab') as f:
                wtr = csv.writer(f, delimiter= ',')
                wtr.writerow(dataRows)
```

```
    except Exception as e:
        print e
    del f, wtr
    # if the iteration matches the random number, export the sample data set for visual-
ization purposes
    try:
        if number == randomNumb:
            out_name = "%s_random_%s" %(ptsName,number)
            arcpy.FeatureClassToFeatureClass_conversion(ptsName,workspace,out_name)
    except Exception as e:
        print e
    print("--------------------------------------------------------------------")
##
end_time = time.time()
print("Total time elapsed was %g seconds" % round((end_time - start_time),2))
```

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Authors

Ron Wilson is an adjunct faculty member of the Geographic Information Systems Program at the University of Maryland, Baltimore County.

Alex Din is a housing research and GIS analyst with the Maryland Department of Housing and Community Development.

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Evaluation Tradecraft

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Household Survey on Tribal Lands: Frame Building Through Rural Address-Based Sampling and Traditional Enumeration

Carol Hafford
Steven Pedlow
NORC at the University of Chicago

Nancy Pindus
Urban Institute

Abstract

The congressionally mandated Assessment of American Indian, Alaska Native, and Native Hawaiian Housing Needs was a housing needs assessment designed to produce national-level estimates of housing needs in U.S. tribal areas (HUD, 2017a). Special care was taken so that the process would not only be technically effective (to ensure reliable results) but also be fully acceptable to the tribes involved. The foundation for the in-person household survey was the development of the sample frame of eligible American Indian and Alaska Native (AIAN) households from which to derive national estimates of housing needs. Three methods were used to construct the list of AIAN households and addresses for the sample frame and to select the households to interview: (1) United States Postal Service address lists, (2) tribal maps and lists, and (3) in-person enumeration. Use of these methods yielded sufficient coverage to provide reliable estimates of housing needs.

Introduction

The *Assessment of American Indian, Alaska Native, and Native Hawaiian Housing Needs* was designed to study housing needs in U.S. tribal areas. The previous similar assessment was conducted in 1996, prior to the passage of the Native American Housing Assistance and Self-Determination Act of 1996[1] that fundamentally changed the way federal funding for housing is delivered to Native people.

This study was a 6-year effort, from 2011 to 2017, that included consultations with tribal leaders, analysis of U.S. Census Bureau data and U.S. Department of Housing and Urban Development (HUD) administrative data, three surveys, and site visits. The most important new data collection effort in this project was a major in-person household survey in a sample of American Indian and Alaska Native (AIAN) tribal areas. This effort was one of the largest and most complex surveys ever undertaken in Indian country. A nationally representative survey of tribally designated housing entities was also conducted.

The study team took special care to make the process technically effective (that is, to ensure reliable results) and also fully acceptable to the tribes involved. All tribal areas, as defined by the Census Bureau, with an AIAN-alone[2] population of at least 150 were eligible for selection. The minimum of 150 was to make sure that a sufficient number of interviews (approximately 30 eligible AIAN households) could be collected from each selected tribe to develop the national estimate, with a proportionally greater number collected from the largest tribes, including the Navajo and Cherokee Nations. The tribal area probabilities were derived from the AIAN-alone population in the 2010 census. From a sample of 595 eligible tribes, the research team selected two embedded representative samples: (1) a representative sample of 120 tribal areas that included the tribally designated housing entities sample; and (2) a representative subsample of 60 tribal areas that included the 40 tribal areas for the household survey and also 20 tribal areas as a reserve, if needed, to replace any of the original 40 sampled tribal areas. The team selected with certainty 7 tribal areas with populations greater than 15,861 AIAN-alone persons for the household survey: (1) Navajo Nation reservation and off-reservation trust land, (2) Cherokee Oklahoma Tribal Statistical Area (OTSA), (3) Lumbee State Designated Tribal Statistical Area, (4) Muscogee (Creek) OTSA, (5) Choctaw OTSA, (6) Chickasaw OTSA, and (7) the Oglala Sioux Pine Ridge Reservation.

After participating in the tribal consultations that HUD held in 2012, the research team worked closely with tribal leaders in each of the 40 tribal areas selected for the household survey to obtain permission to conduct the study. This process ensured tribal stewardship and oversight of any research conducted on sovereign lands while safeguarding community wellbeing and protecting the community from harmful research (Sahota, 2007). Each tribe participating in the study had different protocols and requirements. In nine cases, it was necessary to obtain approval from the tribe's Institutional Review Board and from the tribal government. Ultimately, 37 originally selected

[1] Pub. L. 104–330, 110 Stat. 4016. October 26, 1996.

[2] *AIAN alone* is defined as people reporting that they belong to a single race (American Indian or Alaska native), not in combination with any other race, on the census form.

tribes and 1 replacement tribe in the sample agreed to participate.[3] They included reservation-based tribes; large and small pueblo, woodland, and coastal tribes; tribal jurisdiction service areas in Oklahoma; and native villages in Alaska.

Using tribal-specific sample frames, AIAN households were selected for interviews.[4] In-person interviews were conducted with 1,340 households. This article focuses on the development of the household sampling frame in those selected tribal areas. We describe the procedures used and the experiences of this survey in order to guide other researchers working in tribal or in rural areas. Information for each sampled tribe, including their total populations based on the 2010 census, their AIAN-alone populations, the selection probability, the frame method used, estimated coverage, and the unweighted and weighted response rates are in the technical appendixes to the final report (HUD, 2017b).[5]

The Methodological Challenge

The foundation for the in-person household survey was the development of the sample frame of eligible AIAN households from which to derive national estimates of housing needs. However, no such national frame across tribal areas exists. The research team's experience with data collection in Indian country suggested at the outset that constructing an address-based list of households for each tribal area would be necessary to form the universe from which to draw the sample.

The advantages of using address-based sampling for probability-based surveys include increased coverage of households and access to cost-effective and timely sampling frames (AAPOR, 2016). However, coverage is not evenly distributed for some rural geographies or subpopulations, such as tribes, which can result in undercoverage errors, through either omissions or erroneous exclusions (O'Muircheartaigh, English, and Eckman, 2007). Use of general delivery postal addresses remains common in rural areas, including Indian country; one of the drawbacks of in-person household surveys is that post office box addresses and other rural route addresses are not locatable. Although many tribes have mapped locatable housing units for emergency response services and have assigned households with city-style addresses (that is, a house number and street name), others are still in the process of doing so. Consequently, once the sample of tribal areas was drawn, the research team had to identify alternative sources and methods for developing high-quality, tribal-specific sample frames to select and locate households for a hard-to-reach population within the time and cost parameters of the study.

Creating the Household Sampling Frame

Building the address-based, household-level sampling frame required multiple methods. Many households on tribal lands rely on post office box addresses and other rural route addresses, which

[3] A sample of 40 tribal areas originally was selected, but HUD deemed that 2 tribal areas were ineligible because they were not Indian Housing Block Grant program grantees.

[4] Tribal member households were those households in which the owners or renters, their spouses, or custodial children age 17 or younger self-identified as Native American or Alaska Native, alone or multiracial.

[5] See Exhibit E.1. Summary of 40 Selected Tribal Areas for Household Sample (HUD, 2017b).

do not provide a physical location for data collection. Taking this factor into consideration, the team used three methods to construct the list of AIAN households and addresses for the sample frame and to select the households to interview: (1) United States Postal Service (USPS) address lists, (2) tribal lists, and (3) in-person enumeration. Use of each method involved outreach with each tribe to discuss appropriate procedures and protocols.[6] The research team conducted a pilot test with 15 tribes to assess the feasibility of each approach, taking into consideration the density of the population, the ratio of the AIAN population to the total population (to forecast the level of screening needed), potential access to a tribally held list, the extent of the tribal terrain to cover, and the time and costs involved.

Of the 38 tribal areas, USPS address lists were usable for 9 tribal areas (24 percent). These address lists were used only if the estimated coverage was at least 80 percent. Coverage was determined by dividing the number of city-style addresses within the tribal area by the number of occupied housing units according to the 2010 census.

For another 16 tribal areas (42 percent)—which included land-based reservations, joint-use areas claimed by multiple tribes, OTSAs, and Alaska Native village statistical areas—the study team obtained a single source of housing units or eligible persons, provided by the tribe, to develop the tribal-specific sample frame. These sources varied and included maps of housing units and roads, spreadsheets and printouts of housing units, 911 or fire lists, and tribal membership lists. Gaining access to these lists involved extensive outreach with tribal leaders and tribal departments. Using a structured protocol, the research team consulted with relevant tribal entities to understand the content and quality of the lists or maps (that is, data fields, frequency of updating, percentage of population included, omissions, and so on) and assessed their utility and limitations as sampling frames. Once the quality of the lists or maps was determined, the team needed tribal consensus to share the lists. The research team then negotiated access through multiple entities, including tribal leaders, councils, housing authorities, and others. Use of these proprietary tribal resources was bound by strict confidentiality requirements.

For 12 tribal areas (32 percent), using USPS or tribal-specific lists was not possible. Therefore, housing units in selected blocks within tribal areas were systematically enumerated (listed) in person by field personnel to form the sampling frame. The team conducted listing on large and small land-based reservations, on pueblos, across OTSAs, and in Alaska Native villages. The 38th tribal area, a land-based reservation divided across two states, provided a county-based housing unit list for the portion in one state, but the portion in the other state needed to be listed.

Experienced field interviewers were trained in the enumeration methods. Maps, to help them find the selected areas, were prepared using census geography and MapMarker® software. Driving (sometimes great distances) throughout identified communities across the reservations or tribal areas, interviewers identified and plotted every dwelling in a defined area on a list. Using the list of all housing units identified for a tribal area, statisticians selected a sample of households for the study.

For two reservations, the research team used a list-and-go methodology to expedite the sample frame development-and-selection process, as permission to conduct the data collection was obtained in the final months of the field period. Instead of enumerating (listing) all units in the field, survey

[6] HUD (2017b), exhibit E.1 shows the frame used for each of the 38 tribal areas.

methodologists developed listing sheets based on geocoded maps that identified preselected housing units for each block at a specified sampling rate (this rate depended on the tribal area). Field interviewers received training before starting the list-and-go process and were monitored and coached throughout the listing activity. They were responsible for enumerating the area, screening eligible households, gaining cooperation, and conducting the in-person interviews with AIAN respondents.

The largest tribal area in the study, the Navajo Nation reservation and off-reservation trust land, contains more than 17 percent of the entire AIAN-alone population in tribal areas. With no maps or lists of rural-based addresses available for sampling purposes, listing was necessary. For the Navajo Nation, the research team first selected 15 chapters, or local jurisdictions, before selecting two segments within each chapter. Chapters were selected across five regions, with probabilities proportional to the AIAN population in those areas. The exception was that, within the western region, the Cameron chapter was selected with certainty by request of the Navajo Nation to include households affected by the Bennett Freeze area.[7] No chapters were large enough to be selected with certainty. Within chapters, segments of blocks were selected using census block housing unit counts so that the sample would be representative of all Navajo chapters. Partial or entire block groups (all census blocks with the same first digit within a census tract) were selected that contained approximately 100 to 150 housing units, according to 2010 census data. The research team listed 11 of the 15 chapters in this manner and conducted household interviews. Due to time limitations, interviews with 4 of the 15 chapters were not started before project closedown.[8]

Sampling and Selection Probabilities

When an address-based USPS list or a tribal list of households or persons was available as the sampling frame, the selection probability was very simple—the number of selected housing units divided by the total number of eligible housing units on the list. Determining the number of housing units to select was based on a nonvacancy rate of 85 percent, a screening completion rate of 90 percent, an interview completion rate of 70 percent, and the tribal area-specific person eligibility rate. Only AIAN residents were eligible, and it was assumed that the tribal area-specific eligibility rate was simply the 2010 census AIAN-only population divided by the total tribal area population.[9]

When no list of addresses was available from the USPS address lists or the tribal list (or if these lists did not provide coverage of at least 80 percent), the research team listed specific areas, or segments, and drew samples from the listed units. Different numbers of segments were selected for different tribal areas, often depending on the tribal area-specific eligibility rate. When this eligibility rate was lower, more housing units needed to be selected, and spreading them over more segments

[7] In 1966, the U.S. Bureau of Indian Affairs placed a development ban on 1.5 million acres of Navajo land, encompassing all or parts of nine western Navajo chapters, in order to promote negotiations over a land dispute between the Navajo and Hopi Nations. Under the ban, Navajo families were not allowed to repair their homes; housing construction and infrastructure projects, including installation of water and power lines, were halted. Thousands of Navajo families lived in substandard housing with no running water and electricity. The Bennett Freeze was lifted in 2009. Community development efforts are under way to build new housing units and develop needed infrastructure.

[8] To compensate for this chapter subsampling, the team adjusted weights within the same region. Further information about the 15 chapters selected and their selection probabilities can be found in HUD (2017b), exhibit E.2.

[9] As noted in HUD (2017b), exhibit E.1.

was preferable. Segments were listed in 11 tribal areas, with the most (22) being listed within Navajo Nation, the largest tribal area (2 in each of 11 chapters). Researchers aimed for segments of approximately 100 housing units to minimize effort and costs while still providing enough housing units for selection. Selection probabilities for listed tribal areas were determined using decennial census counts of housing units to establish the selection probability of the segment, and this was multiplied by the selection rate within the segment.

In the list-and-go procedure, the researchers determined in advance which households would be selected block by block based on the expected number of housing units in each block. If the number of housing units differed from expectations, the team prepared the materials so that any additional housing units had a selection probability equal to all others in the segment.

Household Survey Implementation

The integrated approach to onsite data collection was contingent on completing multiple interrelated activities, including tribal approval to conduct the study; developing the sample frame; drawing the tribal-specific sample; and the recruitment, hiring, and training of tribal field interviewers. Working with 38 tribal nations, the timeline for completing these activities differed, so the research team implemented a staggered data collection schedule. Ideally, the research team forecasted 12 weeks of data collection for the household survey, starting from the time permission was granted and field staff were hired and trained. The research team conducted the tribally designated housing entities telephone survey and site visits to 22 tribal areas during this field period.

With the encouragement of the tribal nations, and to ensure that the household survey was conducted in a culturally competent manner, the research team recruited, hired, and trained tribal members to conduct the interviews. Field interviewers' training focused on contacting sampled households, key respondent rules, gaining cooperation, obtaining informed consent, conducting the interview and the enumerator observation, securely mailing completed paper-and-pencil instrument questionnaires, and quality control procedures.

Each household selected for the survey received an advance package about 10 days before the start date of the field data collection period. The field interviewer mailed or hand delivered (to those with post office boxes) advance letters to all sampled households. After allowing sufficient time for receipt of the materials, the field interviewer telephoned or visited the household to schedule an appointment to conduct the in-person interview and assess the exterior conditions of each housing unit. Field interviewers recorded each attempt to contact a household. Interviewers varied contact attempts to the selected households during times household members were most likely to be home.

In many tribal areas, the low density of the AIAN population relative to the non-Native population required extensive screening by field staff to identity eligible AIAN households. For example, extensive screening was necessary for seven of the eight Oklahoma tribes in the sample, as they lack reservations and the American Indian population is dispersed throughout tribal jurisdiction service areas.

After addressing initial questions or concerns, the field interviewers conveyed the need to conduct interviews in respondents' homes to ensure privacy and to conduct the enumerator observation of exterior housing conditions. Depending on tribal protocols, AIAN heads of household or alternate respondents provided informed verbal or written consent to participate in interviews. As with the information letters and brochures, the content of the consent form was tailored to different tribal research conditions or Institutional Review Board requirements.

Interviews focused on how residents viewed their own housing conditions. A key element of administering the household survey was to obtain a complete roster of persons living in the household at the time of the interview. This roster was used to assess the degree of overcrowding and the prevalence of doubled-up households being used as a way to afford housing or to avoid homelessness. Topics addressed included housing unit characteristics and conditions (based on the American Housing Survey's worst case housing needs), satisfaction with housing, culturally responsive housing, needed services and amenities in the community, preferences for homeownership, living on tribal lands, attitudes on tribally assisted housing, and household income and housing costs. After completing the in-home interview, the field interviewer conducted the observation of exterior housing conditions, noting the type of structure, access from the road, and the conditions of the roof, walls, windows, and foundation.

A completed interview consisted of responses to all modules and the enumerator observation of housing conditions. At the close of both parts of the interview, respondents received incentives valued at $20. The team informed each tribe about the post-data collection quality-control procedures to ensure that tribes understood the importance of verification calls to respondents.

Fieldwork on the household survey began in July 2013 and was completed successfully in February 2016. Beyond the anticipated challenges of gaining cooperation with a hard-to-reach population, the scale and remoteness of the geography and extreme weather (that is, blizzards, flash floods, and drought-related fires) challenged field interviewers. The overall weighted response rate was 60 percent.[10] Response rates varied across tribes, with 19 tribal areas having weighted response rates greater than 70 percent.

Conclusion

No one source of address-based household lists is available in Indian country. Ensuring sufficient coverage of the population and developing the sampling frame were key methodological challenges for the Assessment of American Indian, Alaska Native, and Native Hawaiian Housing Needs study (HUD, 2017a). The foundation for this nationally representative survey was the development of the sample frame of eligible AIAN households from which to derive national estimates of housing needs. Building the sampling frame necessitated reliance on multiple methods, including use of USPS address lists; maps and lists obtained from tribes; and in-person enumeration on tribal lands, including use of a list-and-go approach as a last resort. Approval from each tribe was necessary to implement these methods on sovereign tribal lands. Ensuring a high degree of coverage and developing a robust sample frame meant representing, mapping, and enumerating tribal communities so that their housing needs could be assessed and that the study team could have confidence in the national estimates derived.

[10] A weighted response rate is reported for nationally representative surveys, because that is an average of the response rates according to the location of the population.

Acknowledgments

This article is dedicated to the memory of G. Thomas Kingsley of the Urban Institute, who served as the Principal Investigator (PI) for U.S. Department of Housing and Urban Development's 1996 Assessment of American Indian Housing Needs and Programs and was the PI in the early years for this study. He was a champion of safe, affordable, and decent housing for all.

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Authors

Carol Hafford is a principal research scientist at NORC at the University of Chicago.

Steven Pedlow is a senior statistician at NORC at the University of Chicago.

Nancy Pindus is a senior fellow at the Urban Institute.

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What Have We Learned From Paired Testing in Housing Markets?

Sun Jung Oh
John Yinger

Correction

The volume 17, number 3 issue of *Cityscape* contained errors in exhibit A-1. The corrected version of the relevant rows in the table follows.

Exhibit A-1

Results of Housing Discrimination Audit Studies (1 of 2)

Authors	Data/ Methodology[a]	Scale	Other Factors Considered With Race/ Ethnicity and Gender	Location, Period, and Market Examined	Main Findings
Ahmed and Hammarstedt (2008)	E-mail correspondence tests Probit model	500 units (500 x 3 = 1,500 e-mails)		Sweden 2007 Rental tests	Arabic males have 21 to 26 percentage points lower probability of being invited to further contacts or to showings than do Swedish males. Swedish males are almost 13 percentage points less likely to be invited to further contacts or to showings than Swedish females.
Hanson and Hawley (2011)	E-mail correspondence tests Probit model	4,728 tests (4,728 x 2 = 9,456 e-mails)	Socioeconomic status using the prose quality of e-mails	10 U.S. cities 2009 Rental tests	African-American renters have 4.5 percentage points lower probability of receiving an e-mail from landlords than do White renters. This difference ranges from over 8 percentage points in Boston and Los Angeles to less than 1 percentage point in Atlanta and Dallas. African-American renters of higher social class experience small and not statistically distinguishable racial discrimination.

Exhibit A-1

Results of Housing Discrimination Audit Studies (2 of 2)

Authors	Data/ Methodology[a]	Scale	Other Factors Considered With Race/ Ethnicity and Gender	Location, Period, and Market Examined	Main Findings
Hanson, Hawley, and Taylor (2011)	E-mail correspondence tests	3,153 tests (3,153 x 2 = 6,306 e-mails)		10 U.S. cities 2009 Rental tests	African-American renters are treated less favorably than White renters by landlords. Landlords reply faster, reply with an e-mail that is longer to inquiries made, make formal greetings, and use polite language when replying to e-mail inquiries from a White homeseeker.
Roychoudhury and Goodman (1992)	In-person tests Ordered probit model	569 tests		Detroit, Michigan 1980–1990 Rental tests	For each additional apartment available to an agent, the probability of discrimination against an African-American auditor increases by 0.5 for the number of units withheld and by 0.58 for the number of units inspected.

[a] *Methodology indicates any statistical analysis other than computing gross and net measures or the differences-in-means tests.*

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