# Scaling of Small-Area Fair Market Rents: Evidence on Neighborhood Choices of Voucher Recipients*

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**Abstract**

We study the scaling of Small Area Fair Market Rents (SAFMRs) in the Housing Choice Voucher (HCV) program, nationally mandated in 2018 after the 2011 Dallas pilot. SAFMRs set voucher subsidies at ZIP Code rather than metropolitan levels to reduce poverty concentration. Using 2015–2019 administrative data, we find that SAFMRs shifted households into lower-poverty neighborhoods, but effects were less than half as large as in Dallas. The "voltage drop" reflects differences in baseline rental markets and racial segregation, generating substantial metropolitan-level heterogeneity. White households benefited about three times more than Black households, underscoring racial inequities in policy scaling.

Keywords: Housing Choice Voucher, Residential Mobility, Small Area Fair Market Rents, Science of Scaling

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# 1 Introduction

A large body of evidence shows that where families live shapes their children's long-term outcomes. Research has shown that moving to lower-poverty neighborhoods increases college attendance and adult earnings, which explains a significant share of the Black-White earnings gap (Ludwig et al., 2013; Chetty, Hendren, and Katz, 2016; Chetty and Hendren, 2018; Chyn, 2018; Aliprantis and Richter, 2020; Chyn and Katz, 2021). However, despite more than $60 billion in annual federal housing assistance spending, an increasing share of Housing Choice Voucher (HCV) households still reside in high-poverty tracts, which motivates policies aimed at improving access to lower-poverty neighborhoods (Ellen, Horn, and Schwartz, 2016; Pollakowski et al., 2022; Ellen, O'Regan, and Harwood, 2023).[1]

U.S. Department of Housing and Urban Development (HUD) first piloted Small Area Fair Market Rents (SAFMRs) in Dallas in 2011 following a court settlement aimed at reducing voucher concentration in high-poverty neighborhoods. The key policy innovation was to calculate subsidy caps at the ZIP Code level rather than at the broader metropolitan level.[2] This design was expected to expand the stock of voucher-eligible units in higher-rent, opportunity-rich neighborhoods while reducing incentives to cluster in lower-rent, high-poverty tracts. Evidence from the Dallas pilot confirmed these expectations: voucher households substantially reduced their exposure to neighborhood poverty (Collinson and Ganong, 2018). Motivated by Dallas's apparent success, HUD announced in 2016 that Public Housing Authorities (PHAs)[3] in 24 metropolitan areas would be required to adopt SAFMRs by April 2018,[4] with

[1] Explanations include uncertain private benefits (Dastrup, Finkel, and Ellen, 2019; Bergman et al., 2024), family networks and social capital (Horn, Ellen, and Schwartz, 2014), discrimination (Christensen and Timmins, 2022), and high search costs (Galiani, Murphy, and Pantano, 2015; Aliprantis, Martin, and Phillips, 2022).

[2] The previous maximum HCV rents determined at the metropolitan level were called Fair Market Rents (FMRs) and set at the 40th percentile of asking rents for each bedroom size in a metropolitan area, estimated by HUD annually.

[3] The HCV program is administered by state or local PHAs, which retain discretion over implementation details such as inspection frequency and subsidy schedules.

[4] Mandated areas were chosen using four criteria: number of vouchers, concentration of recipients in low

the mandate later extended to an additional 41 metropolitan areas in 2025. Yet, moving from a pilot to large-scale implementation often induces a "voltage drop"—policy impacts attenuate when transplanted into new contexts with different institutional capacities and market conditions (List, 2022; List, 2024). The nationwide rollout in 2018 thus created a unique opportunity to test whether the benefits of the Dallas pilot scaled successfully across diverse metropolitan environments—or whether, consistent with scaling science, the gains would attenuate when exposed to broader variations.

Using confidential HUD administrative records from 2015–2019 that tracked voucher households at the contract–month level, this paper evaluates whether HUD's 2018 SAFMRs mandate reduces overall HCV households' neighborhood-poverty exposure. Specifically, we focus on continuing voucher households, defined as those that have completed at least one annual renewal and account for roughly 98 percent of program participants in any sample year (2015–2019).[5] We test whether SAFMRs sufficiently incentivize recipients to move toward lower-poverty census tracts and alter their annual mobility rate. We then analyze how these effects vary by race and across metropolitan areas to better understand underlying heterogeneity when scaling similar programs in the future.

The causal interpretation of our estimates faces three main threats to identification: (i) non-random selection of the mandated metropolitan areas, (ii) PHAs' discretion over the speed of implementation within those metropolitan areas, and (iii) households' potential to time their lease renewals around the policy. We address these identification challenges by exploiting an institutional detail of the program and the payment-standard timestamps in HUD's administrative records, which helps us to identify in each contract month such that

income neighborhoods, availability of units in high-rent ZIP Codes, and overall vacancy rates.

[5]By using household–contract month level data, we categorize the sample into newly allocated voucher recipients—who account for about 2% of all recipients each year and have only recently entered the dataset—and continuing recipients. These two groups differ in their location choices—new recipients generally lease in higher-poverty neighborhoods compared to existing voucher holders (Appendix Table D1)—as well as in their mobility patterns, including lease up quick in a unit to secure the voucher within the leasing window (Susin, 2002; Eriksen and Ross, 2013; Eriksen and Ross, 2015).

whether a household was subject to SAFMRs or to the pre-existing FMR schedule. Crucially, we restrict the analysis to continuing voucher households—those whose next renewal date is mechanically fixed to the anniversary of their initial lease—so the timing of recertification cannot be manipulated in response to the policy. Although the mandate was scheduled to begin in April 2018, PHAs phased in SAFMRs at different speeds and, importantly, never disclosed exact rollout dates to tenants. Without that information, households had no opportunity to anticipate or manipulate the timing of moves or renewals. Consequently, contract-level switches from FMRs to SAFMRs provide plausibly exogenous variation in payment standards relative to households' evolving mobility decisions.

The results reveal nuanced patterns: switching to a SAFMR-based payment standard through the HUD's 2018 mandate affects where voucher families move, not whether they move. Across mandated metropolitan areas, movers under SAFMRs locate in tracts whose 2010 poverty rates are, on average, -1.22 percentage points (about 5 percent) lower than comparable leases under the old policy —about 0.10 Standard Deviations (SD) reduction, given 2017 tract variation. The annual mobility rate of continuing recipients falls by less than half a percentage point, a statistically detectable but economically negligible change. In short, SAFMRs leave the volume of moves largely intact while steering movers toward higher-opportunity neighborhoods, indicating that the policy maintained efficacy on the intensive margin but not the extensive margin of mobility.

However, the gains are uneven. White voucher holders achieve neighborhood poverty reductions roughly three times greater (–0.19 SD) than those achieved by Black households (–0.06 SD), despite White recipients moving less often. These disparities persist after conditioning on income, family composition, and age, echoing evidence that minority households face steeper search costs, tighter information frictions, and discriminatory barriers that restrict access to low-poverty areas. Because White recipients already lived in areas of somewhat lower poverty before the mandate, the race-neutral design of the SAFMRs leaves

the baseline gaps largely intact. This highlights that scaling ostensibly neutral policies can amplify inequities unless accompanied by complementary interventions—such as counseling, enforcement of source-of-income protections, and targeted landlord outreach—that ensure benefits are more equitably distributed across subgroups.

Overall, compared with the Dallas pilot—where SAFMRs reduced neighborhood poverty by 0.23 SD (Collinson and Ganong, 2018)—the 2018 nationwide rollout yields a more muted average effect of –0.10 SD, illustrating the classic voltage drop in which program impacts attenuate as local frictions and implementation capacity vary across scaling contexts (List, 2024). Specifically, the average effect masks striking cross-metro heterogeneity: some metropolitan areas show sizable poverty declines, while others show little change or even small increases. We document that SAFMRs work best where vouchers were initially clustered in high-poverty tracts and where many units became newly affordable once ZIP code–level ceilings exceeded metropolitan FMRs. By contrast, pronounced pre-existing racial segregation and constrained rental markets attenuate effectiveness.

This research contributes to at least three existing strands of literature. First, our multi-metropolitan evidence enriches the literature on scaling, which stresses how impacts can fade or even reverse when pilots expand to new contexts (Allcott, 2015; Pritchett and Sandefur, 2015; Kline and Walters, 2016; Banerjee et al., 2017; Muralidharan and Niehaus, 2017; Bold et al., 2018; Vivalt, 2020; Egger et al., 2022; List, 2022; Al-Ubaydli, Lai, and List, 2023; List, 2024). By tracking SAFMRs adoption across mandated metropolitan areas, we show how local market conditions and PHA implementation choices shape aggregate outcomes and can blunt policy effectiveness. In doing so, our evidence provides a rare large-scale test of housing policy transportability and highlights how local frictions and institutional environments govern whether pilot-stage successes survive at scale (Reina, Acolin, and Bostic, 2019; Bergman et al., 2024).

Our second contribution speaks to the literature linking voucher design to location choice,

and to mounting evidence on why many low-income families remain in high-poverty areas despite richer subsidies (Susin, 2002; Ellen, Lens, and O'Regan, 2012; Jacob and Ludwig, 2012; Eriksen and Ross, 2013; Jacob, Ludwig, and Miller, 2013; Horn, Ellen, and Schwartz, 2014; Eriksen and Ross, 2015; Geyer, 2017; Ellen, 2020; Ellen, O'Regan, and Strochak, 2022; Ellen, O'Regan, and Strochak, 2024; Bergman et al., 2024). Redesigning voucher subsidy structures through SAFMRs to better align with local rent distributions has been proposed and shown to be effective at smaller scales (Collinson and Ganong, 2018). Ellen, O'Regan, and Strochak (2025) evaluate newly admitted voucher recipients in 2018 SAFMR-mandated metropolitan areas and show that they successfully lease units in higher-rent, lower-poverty ZIP Codes following adoption. We complement this evidence by examining the much larger stock of continuing voucher households and their mobility decisions, which differ from those of new voucher recipients (Susin, 2002; Eriksen and Ross, 2013; Eriksen and Ross, 2015). To the best of our knowledge, this study is the first multi-metropolitan, household-level test of HUD's scaling of the 2018 SAFMRs mandate for continuing recipients, leveraging HUD administrative data and the local institutional details.

Finally, the growing literature documents how structural barriers limit the mobility of minority households (Horn, Ellen, and Schwartz, 2014; Christensen, Sarmiento-Barbieri, and Timmins, 2021; Christensen and Timmins, 2022; Chan and Fan, 2023; Christensen and Timmins, 2023; Aliprantis, Martin, and Tauber, 2024). Our results echo this pattern: White recipients move less often, but secure larger neighborhood quality gains, whereas Black recipients remain more constrained, implying that payment-standard reforms alone cannot close racial gaps without added search assistance and counseling. More broadly, our findings extend the science of scaling by demonstrating that benefit–cost profiles are not evenly transportable across populations, and that scaling neutral policies can inadvertently exacerbate inequities unless subgroup heterogeneity is explicitly anticipated.

The remainder of the paper is structured as follows. Section 2 provides the institutional

background. Section 3 outlines the data sources, presents descriptive insights, and details our empirical strategy. Section 4 presents the main results, while Section 5 explores MSA-level heterogeneity and the drivers of such heterogeneity. Finally, Section 6 concludes.

# 2 Institutional Background

## 2.1 Housing Voucher Program

Section 8 vouchers, rebranded as Housing Choice Voucher in 1998, cap tenant payments at 30 percent of monthly income; HUD covers the remainder up to a *Fair Market Rents* (FMRs)[6]. Because the same metropolitan-wide cap applies everywhere, households face a steep trade-off between meeting minimum unit standards and accessing better neighborhoods, often settling in low-rent, high-poverty tracts (Susin, 2002; Eriksen and Ross, 2013).[7]

Indeed, housing voucher recipients are much more likely to live in neighborhoods of higher poverty than renters. As shown in Figure 1[8], in the 50 largest US metropolitan areas in 2017 based on the American Community Survey, on average, 57 percent of voucher holders—versus 40 percent of all renters—live in census tracts with poverty rates above 20 percent, an "excess concentration" of 17 percentage points compared to renters (Eriksen, 2021). These patterns highlight a basic limitation of metropolitan-wide payment standards: by constraining the subsidy, they reduce voucher recipients' ability to access neighborhoods similar to those where other renters live.

[6] In 2017 the Chicago metro FMR for a two-bedroom unit was \$1,232. A household earning \$14,000 annually would pay roughly \$350 per month (\$14,000 × 0.30 / 12), and HUD would subsidize the remaining \$882.

[7] Figure D1 Panel A shows the downward-sloping budget line under a single FMR; raising the FMR (Panel B) expands, but does not eliminate, the trade-off.

[8] Figure 1 plots, for each metropolitan area, the share of all renters in high-poverty tracts (x axis) against the additional share of HCV households in those same tracts (y axis), following Dastrup et al. (2018). Metropolitan areas with more renters in high-poverty areas show even larger over-representation of voucher holders.

## 2.2 Small Area Fair Market Rents (SAFMRs)

**Introduction of SAFMRs** SAFMRs originated in the Dallas, TX metropolitan area as part of the 2011 settlement,[9] a fair housing lawsuit alleging that a single FMRs reinforced racial and income segregation. The settlement required Dallas area PHAs to adopt ZIP Code-based payment standards. SAFMRs were calculated from the five-year ACS "40th percentile adjusted standard quality" rent for each ZIP Code, allowing higher subsidies in high-rent neighborhoods[10] while voucher holders continued to pay 30 percent of income.[11] In 2012, five additional PHAs (i.e., Chattanooga TN, Chicago IL, Laredo TX, Long Beach CA, and Mamaroneck NY) volunteered to pilot SAFMRs on a smaller scale of cities (Dastrup et al., 2018).[12]

**Scaling of SAFMRs** In late 2016, HUD announced two significant changes to voucher rent ceilings. First, all PHAs in a metropolitan area were allowed to adopt SAFMRs to determine rent ceilings for HCV recipients starting in the 2017 fiscal year. Second, PHAs in 24 mandated metropolitan areas were required to adopt SAFMRs to determine rent ceilings for all HCV recipients starting in 2018. These mandated metropolitan areas were selected on the basis of the following four specific criteria.[13]

[9] Inclusive Communities Project, Inc. v. Texas Department of Housing & Community Affairs (ICP II), 860 F. Supp. 2d 312, 314 (N.D. Tex. 2012)

[10] Panels A and B of Appendix Figure D1 contrast the uniform FMR budget with the horizontal ZIP code-specific budget under SAFMRs. By tying payment standards to neighborhood rents, SAFMRs flatten the budget line: households can upgrade locations without sacrificing unit quality.

[11] For illustration, a two-bedroom SAFMR in the Chicago metropolitan area ranged from about $680 to $1,630 across ZIP Codes in 2017.

[12] Early demonstration evidence on SAFMRs shows consistent but varied effects. Collinson and Ganong (2018) document that the Dallas pilot led voucher households to move to neighborhoods with lower crime and poverty, with stronger effects than uniformly raising payment standards. Dastrup, Finkel, and Ellen (2019) find that families with children in Dallas, Plano, and other demonstration sites were more likely to lease in higher-rent ZIP Codes, though those remaining in low-rent areas faced higher rent burdens. Reina, Acolin, and Bostic (2019) show mixed results across sites, with some households relocating to lower-opportunity areas after SAFMR adoption. More recently, Park (2024) highlights how SAFMRs increase rents in high-rent neighborhoods while lowering them in low-rent neighborhoods

[13] HUD's selection benchmarks are downloaded from HUD's website, merged in rental units vacancy rate from American Community Survey (ACS) 2013-2009 5-Year estimation. Refer to HUD Final Rule

- Voucher count: At least 2,500 vouchers were in use in the metropolitan area;
- Vouchers concentrated in low-income census tracts: The measure of the percentage of voucher holders living in concentrated low-income areas relative to all renters within these areas over the entire metropolitan area exceeds 155 percent (or 1.55). The percentage of voucher families living in concentrated low-income areas relative to all renters within the area must be at least 25 percent;
- Share of high-rent units: At least 20 percent of the standard-quality rental stock in the metropolitan area is located in ZIP Codes where the Small Area FMR exceeds 110 percent of the metropolitan FMR.
- Rental unit vacancy rate: The vacancy rate in the metropolitan area is higher than 4 percent.

HUD mandated the use of SAFMRs by PHAs in the 24 metropolitan areas starting no later than April 11, 2018, although the pace of implementation differed between PHAs, which will be investigated in detail in Section 3.2.[14] Subsequently, in October 2023, HUD expanded this requirement to an additional 41 metropolitan areas, with implementation effective January 1, 2025.[15]

on SAFMRs, November 16, 2016 for more details.

[14]To the best of our knowledge, relatively few papers have examined the implemenation of mandatory SAFMRs starting in 2018. Ellen, O'Regan, and Strochak (2025) find that the new voucher holders, those who entered the program for the first time, successfully moved to higher rental areas without adversely affecting the lease rates of these new recipients. Meanwhile, Aliprantis, Martin, and Phillips (2022) focus on landlord responses to the 2018 SAFMRs in Washington, D.C., finding minimal changes in landlord background check processes and only a small-scale response to the new policy in general.

[15]See the list of the 2025 mandatory metropolitan areas in the Appendix Section B.

# 3 Empirical Setting

## 3.1 Sample Construction

**HUD's Administrative Data** The administrative data on voucher recipient attributes and locations used in this study were obtained from HUD's Office of Public and Indian Housing Information Center, under a restricted data use agreement. Using a household-level identifier, the records track each household's information at every contract anniversary—once a participant is admitted, undergoes an annual renewal or re-examination, or exits the program—yielding household-contract month panel data. The files include annual information on residential address, family composition, demographics, and addresses for individuals who used a housing voucher between January 2015 and December 2019. Additionally, they report detailed contract data: admission and allocation dates, contract start or renewal dates, the administering PHA, and the associated subsidy amounts and rents. Consistent with HUD's selection criteria, some of the key variables such as census tract poverty rates come from the American Community Survey. Of the 24 metropolitan areas mandated by HUD to adopt SAFMRs in April 2018, our mandated sample includes the 15 listed in the Appendix Table A1.[16]

**Continuing Voucher Recipients** Using the household-level identifier in HUD's administrative files, we construct a panel that follows each HCV household over time. This design distinguishes new entrants—households receiving a voucher for the first time—from continuing recipients, who have already renewed their contracts at least once.[17] Our analysis focuses

[16]Nine metropolitan areas were excluded because (i) five have too few usable voucher records in our administrative data, (ii) three had already implemented SAFMRs (or lie adjacent to pre-treated areas) before the mandate took effect, and (iii) one operates under a Move-to-Work waiver that substitutes its own two-tier payment-standard schedule. Appendix A.3 documents these exclusions in detail.

[17]The two groups differ in terms of poverty exposure and other demographic characteristics, including household head's race, gender (female), presence of children, age of the household head, and household size, as shown in Appendix Table D1.

on the latter group, which represents more than 98 percent of program participants in any given year and whose mobility decisions are closely related to lease renewals and standard adjustments of incremental payment. We classify a continuing voucher recipient as having moved when the address on their previous contract record differs from the address on their current contract. More details on sample construction and variable definitions can be found in the Appendix A.1.

**Classifying Payment Standards** Because the original HUD records lack an indicator showing whether the payment standard at a given time is based on SAFMRs or FMRs, a key empirical challenge is determining whether a household's subsidy payment standard in any contract-month is based on metropolitan FMRs or SAFMRs. Even in areas covered by the April 2018 SAFMRs mandate, the exact date on which PHAs began applying the SAFMRs is only observable when updating household records (e.g., lease contract renewal). Consequently, indiscriminately treating every household in mandated metropolitan areas as SAFMRs impacted after April 2018 would introduce measurement error.

To resolve this issue, we developed an algorithm that pinpoints the first year-month in which SAFMRs were actually applied. Using a HUD-provided variable that records the dollar amount of payment standard benchmark for each voucher, we compare that amount with HUD's published SAFMRs for the corresponding ZIP Code. If the two values match, we classify the observation as SAFMR-based; otherwise, it is treated as FMR-based. To our knowledge, this creates the first household-level panel that cleanly distinguishes true SAFMR recipients from otherwise comparable FMR households. Full details are provided in the Appendix A.6.

**Summary Statistics** Column (1) of Table 1 summarizes 2017 voucher holders in the mandated metropolitan areas (175,556 household-month observations). On average, they

live in census tracts with a poverty rate of 23.1 percent; however, 46.1 percent reside in tracts below the 20-percent threshold. Household heads are predominantly Black (67.2 percent), and 58.5 percent of households include at least one child. The mean adjusted monthly income is just $1,218, well under HUD's eligibility cap.[18] Finally, 14.5 percent of recipients change address in a given year, with a median move of 2.77 miles.

## 3.2 Descriptive Insights

In this section, we present descriptive insights that guide subsequent empirical analysis.

**PHAs' SAFMRs Adoption Patterns** As described in Section 2, as of 2017 all PHAs have had the option to use SAFMRs when setting voucher payment standards. Figure 2 plots the monthly adoption rates of SAFMRs (using our algorithm) at the PHA level during 2017 and 2019. Panel A shows that in the 50 largest non-mandatory metropolitan areas virtually no PHA adopted SAFMRs on its own. Panel B confirms a similar near-zero rate in mandated metropolitan areas before the April 2018 start date, after which adoption climbed rapidly: most PHAs surpassed 90 percent compliance within a year, although the pace of rollout differed between agencies.

The absence of voluntary uptake and the lag in adoption among some PHAs, even after the mandate, likely reflect limited administrative capacity—especially the need for upgraded software that links each unit's address to the correct rent ceiling at the ZIP Code level. Unlike earlier 2011 and 2012 demonstrations, the 2018 mandate came without the $50,000 implementation grants that had funded staff training and system upgrades.[19] This anecdotal

[18] Eligibility for Housing Choice Vouchers is primarily based on metropolitan specific income, family size, citizenship or eligible immigration status, and sometimes criminal history. For more details, see HCV Applicant and Tenant Resources .

[19] PHAs receive a flat administrative fee per voucher (see Housing Choice Voucher Program CY 2023 Administrative Fee Rates). This fee is not indexed to higher SAFMRs payments. Although the administrative fee is linked to local federal government wage indexes and additional factors, such as program size, benefit load, percentage of households with earned income, rate of new admissions, and distance from the PHA's

evidence underscores the importance of the supply-side threat to voltage drops (List, 2022), which stem from rising implementation costs and result in diseconomies of scale.

**Subsidies under SAFMRs** Figure 3 illustrates the relationship between rental prices at the ZIP Code level (represented as the ratio of SAFMR to FMR) (horizontal axis) and the median value (in each bin) of housing subsidies (vertical axis) for 2017 (blue squares) and 2019 (red circles). Each dot represents the average subsidy for one of the 20 quantiles of the SAFMR/FMR distribution. A clear pattern emerges when comparing 2017 with 2019: lower-rent ZIP Codes (that is, SAFMR/FMR $< 1$) tend to have lower subsidies, whereas higher-rent ZIP Codes show higher subsidies. However, the incremental differences between 2017 and 2019 are smaller than one might expect, particularly in areas of lower rent. One key reason is that existing voucher holders are subject to annual contract renewals, making it difficult for PHAs to promptly reduce payment standards for tenants who remain in place.[20]

**Racial Differences in Neighborhood Selection** Although HCV eligibility depends solely on income thresholds, our data reveal pronounced racial disparities in neighborhood choice. As shown in Table 1, 67 percent of household heads in our sample are Black (including Hispanic Black) and 30 percent are White (including Hispanic White).[21] Despite having higher average monthly incomes, being younger and more likely to have children, Black voucher holders tend to live in neighborhoods with higher poverty rates than their White counterparts (24.45 percent versus 20.40 percent).

Figure 4—which plots the kernel density of neighborhood-level poverty rates in 2017, before the SAFMRs rollout—illustrates this gap: a larger share of White voucher holders

headquarters, factors related to SAFMRs were dropped due to public comments. See HUD Publishes Revised New Administrative Fee Formula.

[20]PHAs can adopt a phase-in approach to protect families who stay put from immediate reductions in payment standards. For instance, a PHA might lower the payment standard from 140 percent of SAFMRs to 130 percent in the first year, to 120 percent in the second, and eventually align it with the PHA standard. See HUD Final Rule on SAFMRs, November 16, 2016.

[21]The results are unchanged when we restrict "White" to non-Hispanic White.

resided in areas where poverty was below 20 percent. Black households also move more frequently, with an annual mobility rate of 16.07 percent compared to 11.63 percent for White households. As Ellen, O'Regan, and Strochak (2024) argues, higher search costs and a narrower set of available units help explain why Black voucher holders face greater obstacles to leasing in neighborhoods of lower poverty. In the sections that follow, we explore how these patterns of racial location choices, together with the introduction of SAFMRs, shape racial differences in neighborhood choices and subsequent outcomes.

**Regional Variation among Mandatory SAFMRs Metropolitan Areas** Although all metropolitan areas HUD required to adopt SAFMRs in April 2018 satisfy HUD's selection criteria, they differ sharply across those criteria (Appendix Table A1). Specifically, program size varies widely (column (1)). Likewise, large cross-metropolitan differences appear in the share of vouchers clustered in low-income tracts (column (2)), the share of units located in high-rent ZIP Codes (column (3)), and the metropolitan-wide rental vacancy rate (column (4)).

Racial residential patterns also exhibit a wide range. In 2017, the share of Black voucher holders living in tracts with poverty rates above 20 percent was between 28 percent in Washington (DC) and 80 percent in Jackson (MS). The corresponding share for White voucher households ranged from 9 percent to 70 percent, producing Black–White gaps that swing from nearly zero (Hartford, CT) to more than 37 percentage points (Philadelphia, PA) (Appendix Table D2). The analyses that follow test whether these stark cross-metropolitan contrasts in program scale, rental market tightness, and racial sorting yield the place-specific SAFMRs effects (Dastrup et al., 2018; Reina, Acolin, and Bostic, 2019).

## 3.3 Empirical Strategy

This section outlines our identification strategy for gauging how the April 2018 SAFMRs mandate altered continuing voucher households' exposure to neighborhood poverty. A simple before-and-after contrast between mandated and non-mandated metropolitan areas would be inadequate, because three forms of non-randomness could obscure the true effect of the mandate on where voucher holders move:

1. **Mandated Metropolitan Areas Selection.** HUD's decision to mandate SAFMRs may have targeted metropolitan areas with unobserved characteristics (e.g., increased voucher concentration in high-poverty tracts), thus confounding treatment with pre-existing trends.

2. **PHAs' Rollout Decisions.** Within each mandated metropolitan area, PHAs introduced SAFMR-based payment standards at different speeds and may have prioritized the households deemed the most (or least) likely to move.

3. **Tenant Timing.** Households intent on moving to higher rent ZIP Code could, in principle, synchronize their moves with the shift from metropolitan-wide FMRs to ZIP Code level SAFMRs at their annual renewal dates.

We mitigate these threats as follows:

1. **Selection of Comparison Metropolitan Areas.** Building on HUD's published eligibility rules, we construct a control group of fifteen "near-mandatory" metropolitan areas that either met all four criteria but were not selected or matched the metropolitan areas treated closely in those criteria. Appendix A.2 and Table A2 detail the selection procedure.

2. **Contract-Level Treatment Coding.** HUD's administrative records report the dollar amount of subsidy payment standard benchmark when each household renews the

contract. We flag households as *treated* in month $t$ if they use a ZIP Code level SAFMR-based payment standard. Otherwise, it is still under the metropolitan-wide FMRs regime. Exploiting this contract-level timing isolates the moment at which each household actually becomes subject to SAFMRs, independent of PHA-level proclamations.

**Identification Assumption** Our identifying assumption is based on an institutional detail of the SAFMRs mandate: the annual renewal date of a continuing household is locked in by the original lease anniversary. Thus, the month in which a household switches from metropolitan-wide FMRs to ZIP Code level SAFMRs —say, January versus September 2018—is mechanically determined by a schedule established long before the mandate and cannot be altered unilaterally by the tenant.

Within the mandated metropolitan areas in our sample (see the Appendix Figure A1 for a map), the PHAs introduced SAFMRs at slightly different speeds, and the PHAs did not announce the exact rollout date to the tenants, as we highlight in Figure 2. Consequently, voucher recipients had little information to time their moves or renewals strategically. Our key identifying assumption is that the timing of a household's switch to SAFMRs is exogenous to household mobility preferences and to any targeting decisions by PHAs or HUD.

**Regression Specification** Our core sample comprises continuing voucher recipients in the 15 mandated metropolitan areas and the 15 near-mandatory comparison metropolitan areas. For household $i$ served in county $c$ (nested within metropolitan area $m$), observed in month $t \in \{\text{Jan } 2015, \ldots, \text{Dec } 2019\}$, we estimate the following contract-level regression:

$$Y_{icmt} = \alpha + \beta\, \mathbf{1}(\text{PayStand=SAFMR})_{icmt} + \eta_i + \delta_c + \zeta_t + \epsilon_{icmt}, \tag{1}$$

where $\mathbf{1}(\text{PayStand=SAFMR})_{icmt}$ is a binary indicator of whether the renewed voucher sub-

sidy of the household $i$ in year-month $t$ is based on SAFMRs (see Appendix A for details). The model includes household fixed effects $\eta_i$, county fixed effects $\delta_c$, and year-month fixed effects $\zeta_t$. This specification compares households in the same county at the same time, differing only in whether their payment standard is derived from the traditional FMRs or the SAFMRs, while controlling for any time-invariant household attributes. Our primary outcome variable is $Y_{icmt}$, the neighborhood poverty rate of household $i$'s surrounding census tract. We measure poverty using time-invariant pre-treatment data (e.g., 2010 census tract level poverty rate from American Community Survey) to reduce concerns that voucher holders themselves might drive neighborhood-level demographic changes. Standard errors are clustered at the county-year-month level to account for correlated shocks within these units. To further validate our main results, we perform multiple robustness checks that leverage alternative identification strategies and address potential confounding factors in Section 4.3.

# 4 Main Results

## 4.1 Full Sample

**Effect on Poverty Exposure** Table 2 reports the estimated effect of using voucher payment standards that are based on SAFMRs on households' neighborhood poverty exposure. The treatment variable is equal to one if the payment standard of a household is determined by SAFMRs. The table presents the intent-to-treat (ITT) estimate (row (a)), the share of voucher recipients who moved in 2017 (row (b)), the treatment-on-the-treated (TOT) estimate (row (c)), and the corresponding standardized effect (row (d)).

In column (1), SAFMRs lower the mean census tract poverty rate experienced by overall voucher households (i.e., including movers and non-movers) by 0.178 percentage points. Following Collinson and Ganong (2018), we divide this ITT effect by the average 2017 move

rate of voucher recipients (0.1454) to obtain the TOT effect for movers:

$$\frac{-0.1780}{0.1454} \approx -1.22 \text{ percentage points.}$$

which translates to 5.28 percentage lower poverty rates than pre-SAFMRs poverty exposures of 23.123.

Dividing this figure by the cross-sectional standard deviation of the poverty rates at the tract level in mandatory metropolitan areas yields a standardized effect of –0.099 (row (d)). In other words, overall, SAFMRs reduced poverty exposure by roughly 0.1 standard deviations (SD) for voucher holders who relocate. For the binary indicator of residing in a tract with poverty below 20 percent (column (2)), the corresponding standardized effect is 0.145.

We compare our 2018 scaling-phase estimates with those from the 2011 Dallas experimental phase evaluated by Collinson and Ganong (2018). Applying our methodology (Section 3.3) to Dallas administrative records for 2010–2013,[22] we obtain a standardized effect of –0.2304 for movers (full ITT and TOT results appear in Appendix Table D5).[23] Thus, on average, the scaling of SAFMRs through the 2018 mandate produced more muted effects than the earlier Dallas experiment, illustrating a classic voltage drop that we examine in greater detail in Section 5.

**Effect on Mobility** Table 3 reports estimates of the impact of SAFMR payment standards on the mobility of existing voucher recipients, measured by any change in address compared

[22]Here, following Collinson and Ganong (2018), we use Fort Worth as the control group and define treatment at the voucher-recipient level as having an SAFMR-based payment standard.

[23]Collinson and Ganong (2018) analyze the Dallas SAFMR demonstration with a difference-in-differences design, comparing mean poverty exposure before (2010) and after (2013) adoption in Dallas (treatment) and Fort Worth (control). Their specification yields a standardized effect of –0.188. Applying the same specification to the 2018 mandated metropolitan areas produces a standardized effect of –0.0767 (Appendix Table C1, Panel B)—a smaller magnitude than under our preferred specification for both Dallas and the 2018 rollout. Nevertheless, the qualitative implications remain consistent with those generated by our main empirical strategy.

with the previous record.[24] Column (1) shows that, on average, the adoption of SAFMRs led to a statistically significant but economically small reduction in overall mobility rates (a 0.38 percentage point decrease). This effect is primarily driven by the 46% of recipients already living in tracts with poverty rates below 20% in 2017 (column (2)), among whom mobility fell by 0.59 percentage points. This decline is not unexpected: recipients in low-poverty neighborhoods (where rents are often higher) have weaker financial incentives to relocate, anticipating that remaining in place will yield larger subsidies if rents rise under SAFMRs. In contrast, for voucher recipients living in tracts with poverty rates greater than 20% in 2017, overall mobility did not change significantly.

Overall, our findings reveal a nuanced policy lesson. While SAFMRs provide financial incentives to move to lower-poverty neighborhoods, their effectiveness for existing voucher recipients depends on two critical margins. The first is whether households move at all, and the second is where they relocate if they do move—both shaped by baseline neighborhood conditions and household mobility constraints.

## 4.2 Effect by Race

In this section, we investigate how the effects of adopting SAFMRs differ between voucher recipients of White and Black household head. As documented in Section 3.2, White voucher households already lived in markedly lower poverty tracts than Black households before adoption of the SAFMRs (58.76 percent of Black voucher holders lived in high-poverty tracts (poverty over 20 percent) versus 43.47 percent of White voucher holder). Because income-eligibility rules and subsidy formulas are identical across races, these pre-existing differences highlight substantial location choice barriers facing Black recipients.

Table 4 quantifies how SAFMRs affect tract-level poverty exposure by race. Column

[24]Note that with a dependent variable as a binary indicator variable of whether or not moving, we control a set of demographic control variables of the household ($\mathbf{X'}_{i,t}$) as shown in Table 1 instead of fixed effects of the household $\eta_i$.

(1) shows a reduction in ITT of -0.27 percentage points for White households. Scaling this estimate by their 2017 move rate (11.63 percent) implies a TOT decline of –2.35 percentage points, or –0.19 SD. For Black households, the ITT is –0.11 percentage points; dividing by their higher move rate (16.07 percent) yields a TOT of –0.71 percentage points, or –0.06 SD. Thus, among movers, White households realize roughly triple the improvement in neighborhood quality enjoyed by Black households. Because our specification includes household fixed effects, time-invariant racial differences in sociodemographic characteristics—such as age, sex, the presence of children, single-parent status, or employment—cannot explain these results.[25]

We interpret these gaps to reflect *destination* constraints rather than *mobility* propensities: Black households actually move more often (16.07% for Black households versus 11.63% for White voucher holders); SAFMRs did not significantly change propensity of moving.[26] However, prior research shows that minority voucher recipients face higher search costs, rely more heavily on networks of the same race, and encounter discriminatory barriers when trying to lease in low-poverty neighborhoods (Horn, Ellen, and Schwartz, 2014; Christensen, Sarmiento-Barbieri, and Timmins, 2021; Christensen and Timmins, 2022; Aliprantis, Carroll, and Young, 2024). These mobility frictions sharply limit the set of low-poverty destinations open to Black households. As a result, even when SAFMRs expand the rental budget for both racial groups, Black movers remain much more likely than their White peers to settle in higher-poverty areas. Consequently, what is formally a race-neutral increase in payment standards yields substantially larger neighborhood gains for White households, while many

[25]For example, as shown in Panel B of Table 1, Black voucher recipients were more likely to have children than White recipients, and mobility constraints and objectives can differ between households with and without children (Ellen, Horn, and Schwartz, 2016; Ellen, 2020). Nonetheless, Appendix Table D4 compares all households with or without school-aged children and shows the results are not driven by this.

[26]Appendix Table D3 describes a modest 0.74 percentage point decline in moves by Black households already residing in tracts with poverty rates below 20 percent; the analogous estimate for White households is smaller and statistically insignificant. In higher poverty tracts, neither group exhibits meaningful mobility changes.

Black movers continue to be constrained to disadvantaged locations.

## 4.3 Robustness Checks

To further validate our main results, we perform multiple robustness checks that take advantage of alternative identification strategies and address possible confounding factors.

**Instrumental Variable Approach** We consider an instrumental variable approach, as an alternative identification strategy. In our main specification, the SAFMRs payment standards for individual voucher holders (i.e., $\mathbf{1}(\text{PayStand=SAFMR})_{icmt}$ in Equation (1)) may be endogenous if, for example, PHAs target implementation of SAFMRs towards households with an explicit desire to move to lower-poverty areas, or to those who would otherwise not move without an extra incentive.

To address this concern, Appendix Table B1 presents two-stage least squares (2SLS) estimates in which we instrument the use of SAFMRs payment standards with the PHA peer-based compliance rate. This compliance rate, defined as the proportion of recipients within a PHA who receive payment standards based on SAFMRs, is highly dependent on the HUD mandate that began in April 2018 and on the capacity (or management practices) of individual PHA, making it unlikely that the situation of a single household would influence overall PHA compliance decisions. Appendix B provides additional details on this instrumental variable strategy, including the validity of the first stage. Overall, the 2SLS results are statistically indistinguishable from our main specifications.

**Alternative Control Group** Finally, we explore the results using alternative control metropolitan areas. Panel A of Appendix Table B2 limits the control group to the metropolitan areas mandated to adopt SAFMRs in 2025, while Panel B further enlarges the pool to include every metropolitan area in our main administrative data sets. In both cases, the esti-

mated standardized effects are smaller in magnitude (-0.073, -0.078) than those in our main specification (-0.099) —an expected attenuation given the looser matching criteria—but they remain statistically significant and of the same sign. Thus, although Panel A and B modestly underestimate the impact of the policy, the substantive conclusion that the SAFMRs lower the neighborhood poverty exposure of voucher holders is unchanged.

# 5 Evaluating the Scaling of SAFMRs

The mandatory expansion of SAFMRs in 2018 can be viewed as a scaled version of the earlier, small-scale demonstration carried out in the Dallas metropolitan area in 2011. The literature on the science of scaling emphasizes that whether the underlying benefit–cost profiles transport to new populations, contexts, and implementation environments (List, 2022; List, 2024). A central concern is voltage drop: policies that deliver large benefits in pilots often attenuate at scale due to heterogeneity in local conditions, institutional capacity, or behavioral responses. Such dependence highlights that policy effectiveness is inherently context-sensitive, and that ignoring this heterogeneity can yield misleading conclusions about whether interventions remain cost-effective once scaled.

Benchmarking against the Dallas pilot, Section 4 and Appendix C show that standardized effects were substantially larger in the pilot than in the 2018 mandate. The muted average for 2018 primarily reflects wide dispersion across metropolitan areas rather than uniform attenuation. We therefore turn to metropolitan-level heterogeneity, identifying systematic factors that shape where and for whom SAFMRs replicate pilot-stage gains versus where they fall short. This approach situates SAFMRs as a natural case study in the science of scaling—illustrating both the promise and the limits of transporting reforms from pilot to policy-relevant scale.

## 5.1 Heterogeneity across Metropolitan Areas

First, we explore the heterogeneity at the metropolitan level between the mandated metropolitan areas for 2018. HUD expanded the mandate of the SAFMRs to 41 additional metropolitan areas by January 2025. Given this potential expansion, understanding the diverse effects and nuances in different metropolitan areas is vital. Each area has its own socioeconomic dynamics, characteristics of the rental market, demographic distributions, and institutional challenges.

Figure 5 Panel A (point estimates presented in Panel C of Appendix Table D5) illustrates the standardized effectiveness of the policy at the metropolitan level, revealing substantial variability in policy success in metropolitan areas. Certain areas, such as Monmouth-Ocean (NJ), North Port (FL), Hartford (CT), Jackson (MS), San Antonio (TX), and Washington, DC, show markedly larger improvements for voucher recipients. In contrast, other metropolitan areas (indicated in red), including Bergen-Passaic (NJ), Charlotte (NC), Jacksonville (FL), and Sacramento (CA), exhibit the opposite effect, suggesting an increase in poverty exposure that is contrary to the intended goals of the policy.

**Effect by Race** Figure 5 Panel B and C presents the effectiveness of the policy by race in each metropolitan area (point estimates presented in Table D6), indicating that the overall standardized effects of White household head voucher recipients are significantly greater (-0.1903) compared to those of Black households (-0.0576). Furthermore, according to Panel B of Figure 5, this racial heterogeneity is especially pronounced in metropolitan areas where the policy was generally less effective, such as Bergen-Passaic (NJ), Jacksonville (FL), Sacramento (CA) and Charlotte (NC). In these locations, positive SAFMRs effects (that is, movements to areas of higher poverty rather than areas of lower poverty) were primarily driven by Black households.

## 5.2 Drivers of Heterogeneity in SAFMR Effectiveness

Explaining why the 2018 SAFMRs mandate generated such divergent outcomes across metropolitan areas is difficult. The variation likely reflects differences in local rental-market conditions, pre-existing racial and economic segregation, voucher-holder search dynamics, the spatial organization of PHAs, and agency-specific administrative constraints. Although we cannot fully disentangle these channels, we examine how selected pre-SAFMR metropolitan-level characteristics correlate with policy effectiveness in the mandated metros.

For household $i$ in county $c$ of metropolitan area $m$ observed in year-month $t$, we estimate

$$Y_{icmt} = \alpha + \beta\, \mathbf{1}\{\text{PayStand}_{icmt} = \text{SAFMR}\} + \gamma\big[X_m \times \mathbf{1}\{\text{PayStand}_{icmt} = \text{SAFMR}\}\big] + \eta_i + \delta_c + \zeta_t + \varepsilon_{icmt},$$

where $Y_{icmt}$ is the poverty rate of the census tract in which household $i$ resides (higher values imply greater exposure to poverty). Thus, a negative $\beta$ or $\gamma$ indicates a decline in poverty exposure. The interaction term combines the SAFMRs indicator with a pre-treatment metropolitan area-level characteristic $X_m$, measured before adoption. Household fixed effects ($\eta_i$), county fixed effects ($\delta_c$), and year-month fixed effects ($\zeta_t$) mirror our main specification; standard errors are clustered at the county–year-month level.

Table 5 considers five metropolitan area-level characteristics ($X_m$). Columns (1)–(4) use the exact metrics HUD employed when selecting metropolitan areas for the mandate; Column (5) uses the 2017 racial gap in voucher-holder concentration in high-poverty tracts—defined as the difference between the shares of Black and White voucher holders living in tracts with at least 20 percent poverty (Appendix Table D2, column (4)).

In each column, the interaction coefficient $\gamma$ shows how the effect of adopting SAFMRs payment standards varies with the level of the corresponding metropolitan-wide characteristic, while $\beta$ captures the baseline SAFMRs effects when $X_m = 0$. To obtain the average

effect of SAFMRs for a particular metropolitan area, insert the value of the characteristic of the metro into the interaction term: $\hat{\beta} + \hat{\gamma}\bar{X}_m$. For the overall average effect: $\hat{\beta} + \hat{\gamma}\bar{X}$, where $\bar{X}$ is the mean of the characteristic reported in the last row of Table 5.

The estimated $\hat{\gamma}$ terms in Table 5 pinpoints which metropolitan characteristics meaningfully amplify or dampen the effect of SAFMRs on the neighborhood poverty exposure of voucher holders:

- Column (2) – Voucher concentration in low-income census tracts: The interaction coefficient ($\gamma$) is negative and highly significant, indicating that metropolitan areas where vouchers are more concentrated in low-income areas see a greater benefit of poverty reduction from the adoption of SAFMRs.

- Column (3) – Share of high-rent units (SAFMR $\geq$ 110% of metropolitan-wide FMR): This interaction is also negative and significant: When a larger fraction of the rental stock becomes newly affordable under SAFMRs, voucher holders are more likely to move into lower-poverty tracts.

- Column (5) – Racial gap in high-poverty exposure: The $\gamma$ is positive and significant, showing that in metropolitan areas with larger Black–White disparities in exposure to high-poverty neighborhoods, SAFMRs yield smaller—and potentially offsetting—poverty reductions.

In contrast, the interaction terms for the program scale (log voucher count, column (1)) and the rental vacancy rate (column (4)) are statistically insignificant, suggesting that SAFMRs effectiveness is largely insensitive to these two factors.

In sum, SAFMRs deliver the greatest poverty-reduction gains in metropolitan areas where vouchers were initially concentrated in low-income neighborhoods and where many units are lifted above FMRs thresholds, while pronounced racial segregation among voucher holders substantially weakens those gains.

# 6 Conclusion

The 2018 SAFMRs mandate provided a rare opportunity to observe SAFMRs implementation at scale, moving well beyond the pilot settings that first motivated the policy. Our findings confirm the core logic of SAFMRs: tying subsidy caps to ZIP Code rents relaxes budget constraints that otherwise push voucher families into lower-rent, higher-poverty neighborhoods. In Dallas, this experimental design delivered large gains, and our multi-metropolitan, scaling evidence shows that similar mechanisms operate nationally, albeit in attenuated form.

On average, movers in mandated metropolitan areas experienced neighborhood poverty reductions of about $-0.10$ standard deviations, less than half the Dallas pilot effect, illustrating the voltage drop that often accompanies scaling. This muted average masks pronounced variation across markets and striking racial disparities: SAFMRs proved most effective where voucher holders had been concentrated in high-poverty tracts and many higher-rent units became newly affordable, yet far less so where segregation and rental tightness constrained access.

Viewed through the lens of the science of scaling, these results underscore both the promise and the limits of a uniform subsidy schedule. The SAFMRs mandate demonstrates that reforms validated in pilots can transport to scale, but that effectiveness depend critically on local contexts such as representativeness and institutional capacity. Moreover, the heterogeneous results across races extend the science of scaling discussion by showing that the policy effectiveness is not evenly transportable across populations, and that scaling-neutral policies can inadvertently exacerbate inequities unless subgroup heterogeneity is explicitly anticipated. Future rollouts should therefore treat SAFMRs as a necessary but not sufficient condition for equitable neighborhood access, coupling payment-standard reforms with complementary supports—mobility counseling, landlord outreach, enforcement of source-of-income protections, and adjustments for local market conditions—to ensure that pilot-stage

gains translate into durable and broadly shared opportunity.

# References


Aliprantis, Dionissi, Daniel R Carroll, and Eric R Young (2024). "What explains neighborhood sorting by income and race?" In: *Journal of Urban Economics* 141, p. 103508.

Aliprantis, Dionissi, Hal Martin, and David Phillips (2022). "Landlords and access to opportunity". In: *Journal of Urban Economics* 129, p. 103420.

Aliprantis, Dionissi, Hal Martin, and Kristen Tauber (2024). "What determines the success of housing mobility programs?" In: *Journal of Housing Economics* 65, p. 102009.

Aliprantis, Dionissi and Francisca G-C Richter (2020). "Evidence of neighborhood effects from Moving to Opportunity: LATEs of neighborhood quality". In: *Review of Economics and Statistics* 102.4, pp. 633–647.

Allcott, Hunt (2015). "Site selection bias in program evaluation". In: *The Quarterly journal of economics* 130.3, pp. 1117–1165.

Banerjee, Abhijit et al. (2017). "From proof of concept to scalable policies: Challenges and solutions, with an application". In: *Journal of Economic Perspectives* 31.4, pp. 73–102.

Bergman, Peter et al. (2024). "Creating moves to opportunity: Experimental evidence on barriers to neighborhood choice". In: *American Economic Review* 114.5, pp. 1281–1337.

Bold, Tessa et al. (2018). "Experimental evidence on scaling up education reforms in Kenya". In: *Journal of Public Economics* 168, pp. 1–20.

Chan, Eric W and Yulian Fan (2023). "Housing discrimination in the low-income context: Evidence from a correspondence experiment". In: *Journal of Housing Economics* 59, p. 101889.

Chetty, Raj and Nathaniel Hendren (2018). "The impacts of neighborhoods on intergenerational mobility I: Childhood exposure effects". In: *The Quarterly Journal of Economics* 133.3, pp. 1107–1162.

Chetty, Raj, Nathaniel Hendren, and Lawrence F Katz (2016). "The effects of exposure to better neighborhoods on children: New evidence from the moving to opportunity experiment". In: *American Economic Review* 106.4, pp. 855–902.

Christensen, Peter, Ignacio Sarmiento-Barbieri, and Christopher Timmins (2021). *Racial discrimination and housing outcomes in the United States rental market*. Tech. rep. National Bureau of Economic Research.

Christensen, Peter and Christopher Timmins (2022). "Sorting or steering: The effects of housing discrimination on neighborhood choice". In: *Journal of Political Economy* 130.8, pp. 2110–2163.

— (2023). "The damages and distortions from discrimination in the rental housing market". In: *The Quarterly Journal of Economics* 138.4, pp. 2505–2557.

Chyn, Eric (2018). "Moved to opportunity: The long-run effects of public housing demolition on children". In: *American Economic Review* 108.10, pp. 3028–3056.

Chyn, Eric and Lawrence F Katz (2021). "Neighborhoods matter: Assessing the evidence for place effects". In: *Journal of Economic Perspectives* 35.4, pp. 197–222.

Collinson, Robert and Peter Ganong (2018). "How do changes in housing voucher design affect rent and neighborhood quality?" In: *American Economic Journal: Economic Policy* 10.2, pp. 62–89.

Dastrup, Samuel, Meryl Finkel, and Ingrid Gould Ellen (2019). "The effects of small area fair market rents on the neighborhood choices of families with children". In: *Cityscape* 21.3, pp. 19–48.

Dastrup, Samuel et al. (2018). "Small area fair market rent demonstration evaluation: Final report". In: *Prepared for the US Department of Housing and Urban Development, Office of Policy Development and Research*.

Egger, Dennis et al. (2022). "General equilibrium effects of cash transfers: experimental evidence from Kenya". In: *Econometrica* 90.6, pp. 2603–2643.

Ellen, Ingrid Gould (2020). "What do we know about housing choice vouchers?" In: *Regional Science and Urban Economics* 80, p. 103380.

Ellen, Ingrid Gould, Keren Mertens Horn, and Amy Ellen Schwartz (2016). "Why don't housing choice voucher recipients live near better schools? Insights from Big Data". In: *Journal of Policy Analysis and Management* 35.4, pp. 884–905.

Ellen, Ingrid Gould, Michael C Lens, and Katherine O'Regan (2012). "American murder mystery revisited: do housing voucher households cause crime?" In: *Housing Policy Debate* 22.4, pp. 551–572.

Ellen, Ingrid Gould, Katherine O'Regan, and Sarah Strochak (2022). "Hidden Tradeoffs or More Opportunity: How Do Small Area Fair Market Rents Affect Housing Voucher Lease-up Rates?" In: *2022 APPAM Fall Research Conference*. APPAM.

Ellen, Ingrid Gould, Katherine O'Regan, and Sarah Strochak (2024). "Race, Space, and Take Up: Explaining housing voucher lease-up rates". In: *Journal of Housing Economics* 63, p. 101980.

— (2025). "Pricing for opportunity: The impact of spatially varying rent subsidies on housing voucher neighborhoods and take-up". In: *Journal of Public Economics* 250, p. 105465.

Ellen, Ingrid Gould, Katherine M O'Regan, and Katharine WH Harwood (2023). "Advancing choice in the housing choice voucher program: Source of income protections and locational outcomes". In: *Housing Policy Debate* 33.4, pp. 941–962.

Eriksen, Michael D (2021). "The Location of Affordable and Subsidized Rental Housing Across and Within the Largest Cities in the United States". In: *Available at SSRN 3912773*.

Eriksen, Michael D and Amanda Ross (2013). "The impact of housing vouchers on mobility and neighborhood attributes". In: *Real Estate Economics* 41.2, pp. 255–277.

— (2015). "Housing vouchers and the price of rental housing". In: *American Economic Journal: Economic Policy* 7.3, pp. 154–176.

Galiani, Sebastian, Alvin Murphy, and Juan Pantano (2015). "Estimating neighborhood choice models: Lessons from a housing assistance experiment". In: *American Economic Review* 105.11, pp. 3385–3415.

Geyer, Judy (2017). "Housing demand and neighborhood choice with housing vouchers". In: *Journal of Urban Economics* 99, pp. 48–61.

Horn, Keren Mertens, Ingrid Gould Ellen, and Amy Ellen Schwartz (2014). "Do Housing Choice Voucher holders live near good schools?" In: *Journal of Housing Economics* 23, pp. 28–40.

Jacob, Brian A and Jens Ludwig (2012). "The effects of housing assistance on labor supply: Evidence from a voucher lottery". In: *American Economic Review* 102.1, pp. 272–304.

Jacob, Brian A, Jens Ludwig, and Douglas L Miller (2013). "The effects of housing and neighborhood conditions on child mortality". In: *Journal of health economics* 32.1, pp. 195–206.

Kline, Patrick and Christopher R Walters (2016). "Evaluating public programs with close substitutes: The case of Head Start". In: *The Quarterly Journal of Economics* 131.4, pp. 1795–1848.

List, John A (2022). *The voltage effect: How to make good ideas great and great ideas scale*. Currency.

— (2024). "Optimally generate policy-based evidence before scaling". In: *Nature* 626.7999, pp. 491–499.

Ludwig, Jens et al. (2013). "Long-term neighborhood effects on low-income families: Evidence from Moving to Opportunity". In: *American economic review* 103.3, pp. 226–231.

Muralidharan, Karthik and Paul Niehaus (2017). "Experimentation at scale". In: *Journal of Economic Perspectives* 31.4, pp. 103–124.

Park, JoonYup (2024). *Improving Access to Opportunity: Housing Vouchers and Residential Equilibrium*. Tech. rep. Working Paper.

Pollakowski, Henry O et al. (2022). "Childhood housing and adult outcomes: a between-siblings analysis of housing vouchers and public housing". In: *American Economic Journal: Economic Policy* 14.3, pp. 235–272.

Pritchett, Lant and Justin Sandefur (2015). "Learning from experiments when context matters". In: *American Economic Review* 105.5, pp. 471–475.

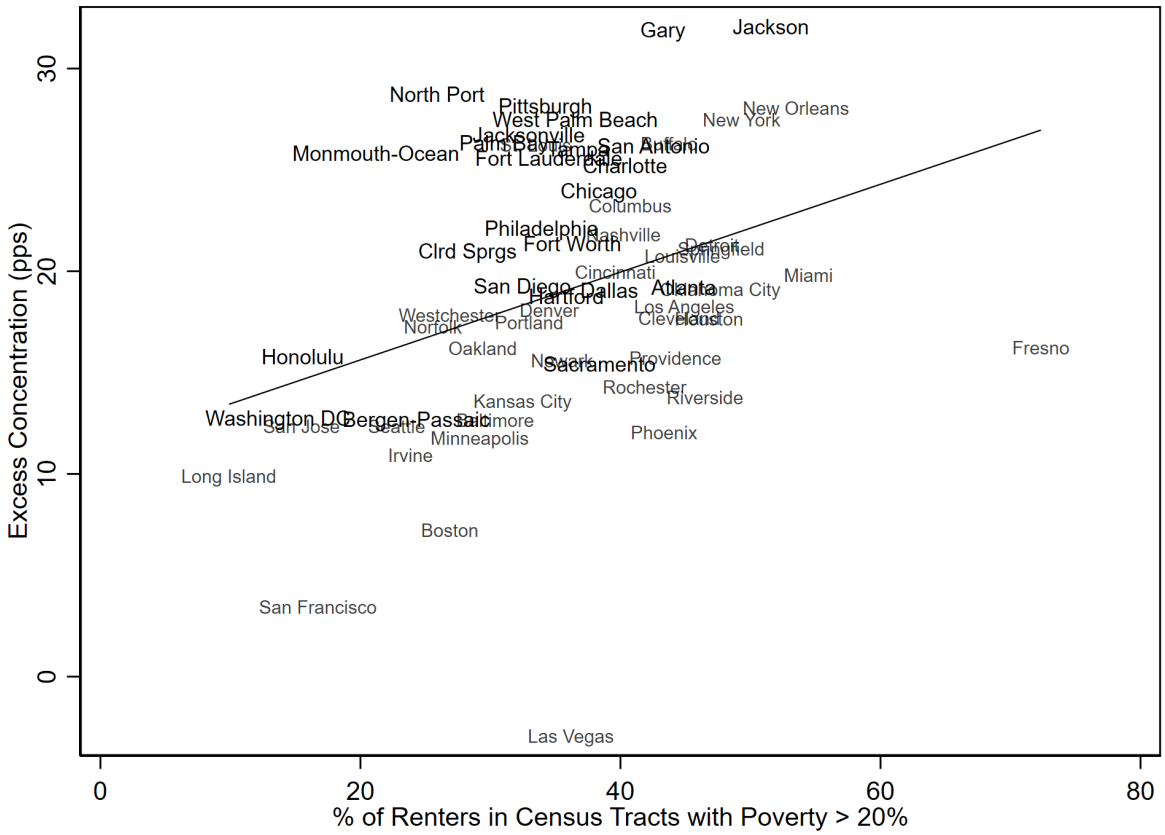
Reina, Vincent, Arthur Acolin, and Raphael W Bostic (2019). "Section 8 vouchers and rent limits: Do small area fair market rent limits increase access to opportunity neighborhoods? An early evaluation". In: *Housing Policy Debate* 29.1, pp. 44–61.

Susin, Scott (2002). "Rent vouchers and the price of low-income housing". In: *Journal of Public Economics* 83.1, pp. 109–152.

Al-Ubaydli, Omar, Chien-Yu Lai, and John A List (2023). *A Simple Rational Expectations Model of the Voltage Effect*. Tech. rep. National Bureau of Economic Research.

Vivalt, Eva (2020). "How much can we generalize from impact evaluations?" In: *Journal of the European Economic Association* 18.6, pp. 3045–3089.

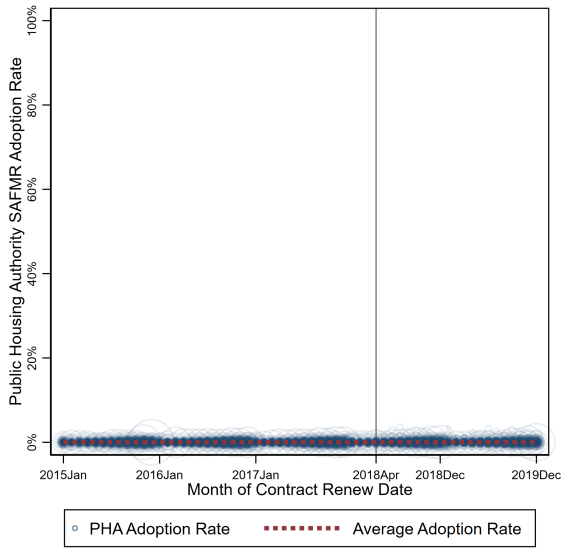
**Figure 1: Excess Concentration of Voucher Holders in High-Poverty Tracts**



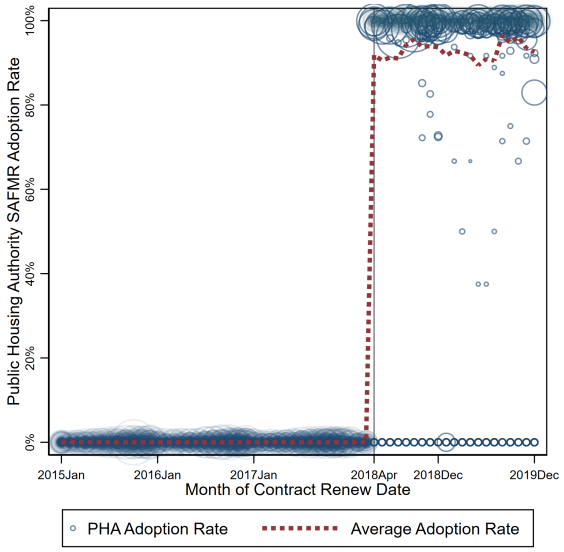

*Notes:* The x-axis represents the percentage of all renters living in census tracts where the poverty rate exceeds 20% for the 50 largest US metropolitan areas in 2017, based on the American Community Survey. The y-axis shows excess concentration, defined as the difference, in percentage points, between the share of Housing Choice Voucher (HCV) recipients in these high-poverty census tracts and the share of all renters (as shown on the x-axis), in the same metropolitan area. Metropolitan areas shown in black indicate those where the use of SAFMRs became mandatory in April 2018, while those in grey represent metropolitan areas where SAFMRs were not mandated.

## Figure 2: SAFMRs Adoption Rate

A. PHAs in Non-Mandatory Metropolitan Areas

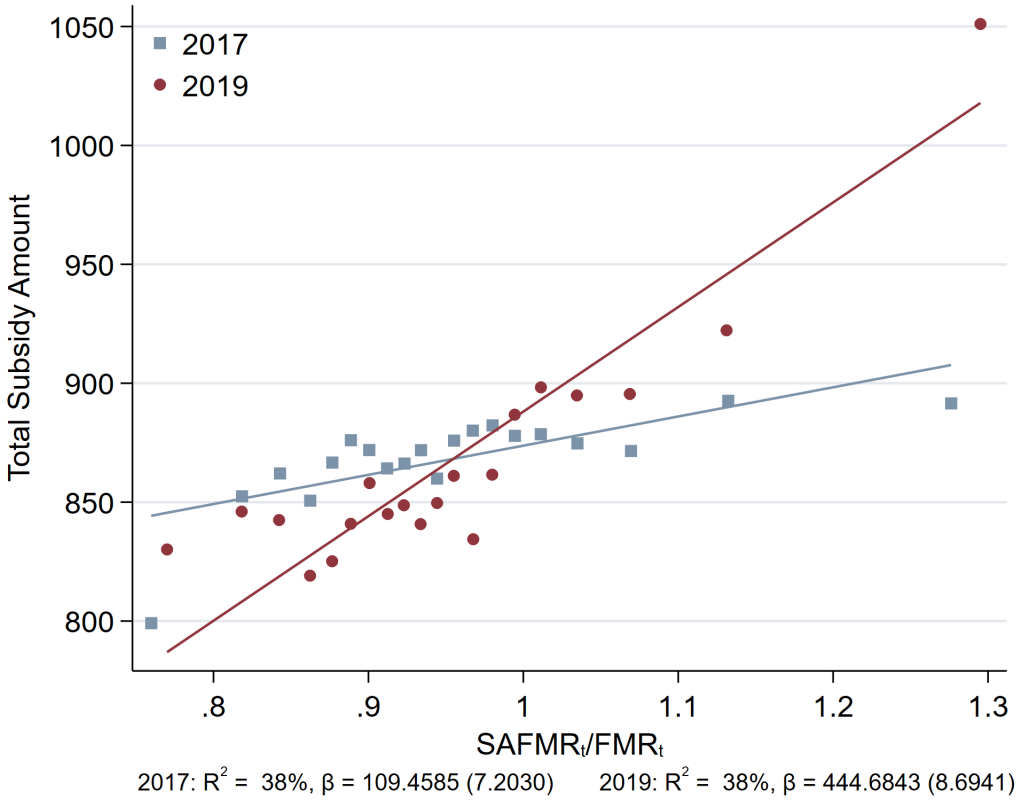



B. PHAs in Mandatory Metropolitan Areas



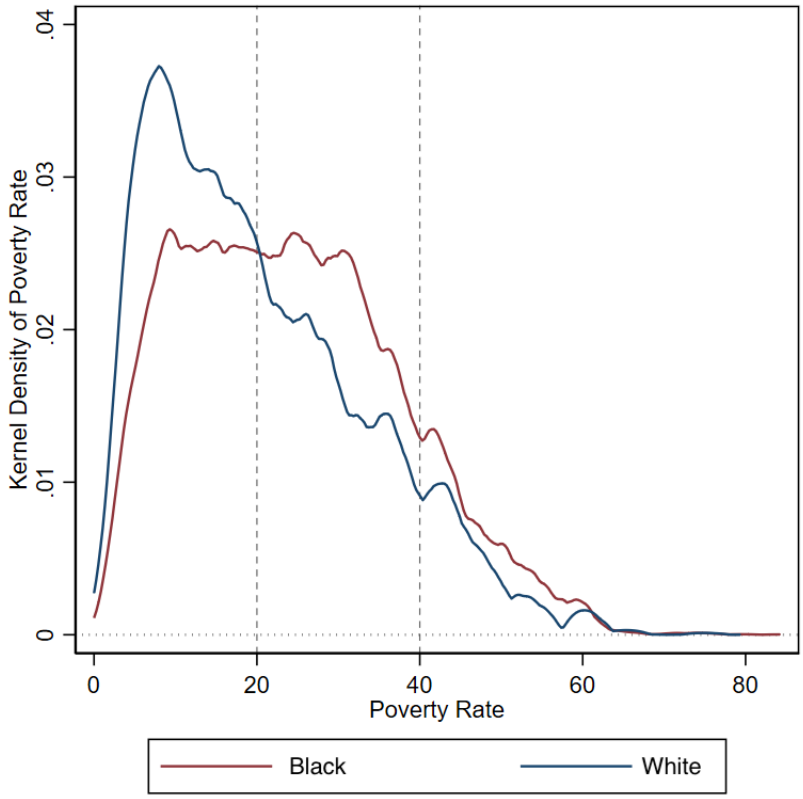

*Notes:* The figures show the SAFMRs adoption rates of each Public Housing Authority (PHA) in the 50 most populous metropolitan areas, by month. The x-axis for Panels A and B represents the contract renewal date of voucher holders, and the y-axis represents the PHA-level SAFMRs adoption rates. PHAs were required to apply SAFMRs-based payment standards after April 2018, for voucher holders with a prior allocation when they renew their contracts. The size of each circle reflects the relative number of housing vouchers renewed by each PHA during that month.

**Figure 3: Housing Subsidy Amount and ZIP code level Market Rent**



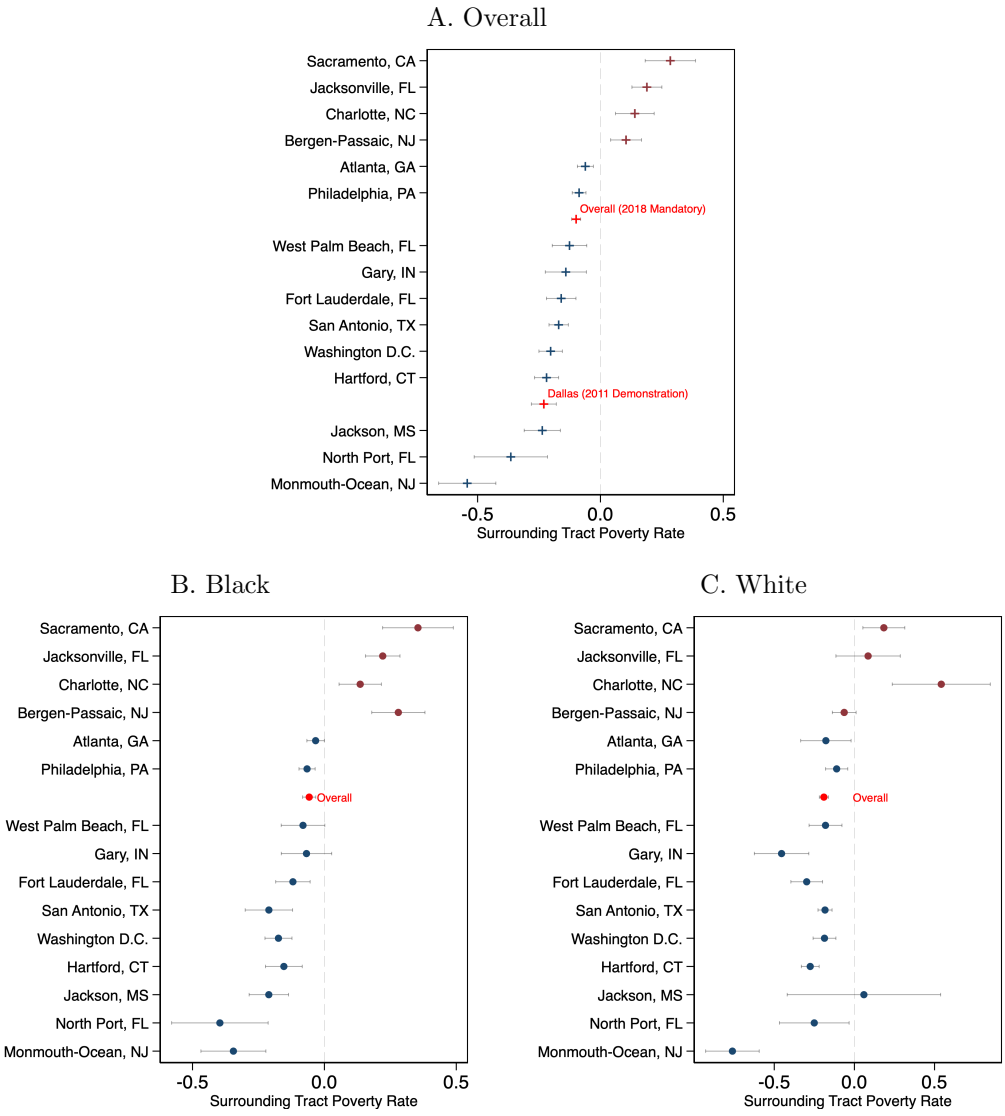

*Notes:* The figure compares the average subsidies between the voucher holders in 2017 and 2019, focusing solely on voucher recipient households in the mandatory metropolitan areas. Each dot on the plot represents the mean value for one of the 20 quantiles of the distribution of ZIP Code level SAFMR/FMR.

**Figure 4: Poverty Rate Distribution of Mandatory SAFMRs Metropolitan Areas, 2017**




*Notes:* The figure shows the distribution (kernel density function) of the surrounding census tract poverty rates for all voucher holders in mandatory metropolitan areas in 2017, by household head race.

## Figure 5: Effect of SAFMRs on Poverty Rate across Metropolitan Areas




*Notes:* The figures plot standardized treatment effects of SAFMRs payment standard on the surrounding tract poverty rate for the metropolitan areas subject to the 2018 mandate and for the 2011 Dallas demonstration, using our main identification strategy described in Section 5.1. Panel A pools all voucher households; Panels B and C restrict the sample to the voucher holders of Black and White household heads, respectively. Negative values denote post-SAFMRs reductions in poverty (i.e., improvement). The grey bars represent 90% confidence intervals. Each 2018 metropolitan area is compared with the non-mandated metropolitan areas described in Section 3; Dallas is compared with the matched PHAs selected in Dastrup et al. (2018). Exact point estimates and standard errors are presented in Appendix Tables D5 and D6.

**Table 1: Descriptive Statistics for Voucher Holders in SAFMRs Mandatory Metropolitan Areas, 2017**

| 2017 Value (Mean) | (1) Overall | (2) Black | (3) White | (4) Difference b/w (2) and (3) |
|---|---|---|---|---|
| *Dependent Variables* | | | | |
| Census Tract Poverty Rate | 23.1230 | 24.4478 | 20.4037 | 4.0441*** |
| <20% Poverty Tract | 0.4609 | 0.4124 | 0.5652 | -0.1529*** |
| Move Rate | 0.1454 | 0.1607 | 0.1163 | 0.0445*** |
| *Voucher Holders Demographics* | | | | |
| Black | 0.6722 | | | |
| Asian | 0.0192 | | | |
| Other Race | 0.0098 | | | |
| Hispanic | 0.1546 | 0.0197 | 0.4553 | -0.4356*** |
| Female | 0.8465 | 0.8855 | 0.7688 | 0.1166*** |
| Kids Present | 0.5850 | 0.6476 | 0.4511 | 0.1965*** |
| Household Member w/ Disabilities | 0.2496 | 0.2221 | 0.3107 | -0.0886*** |
| Age≤30 (Baseline) | 0.1866 | 0.2119 | 0.1375 | 0.0744*** |
| Age 30-40 | 0.2759 | 0.3092 | 0.2073 | 0.1019*** |
| Age 40-50 | 0.2145 | 0.2162 | 0.2096 | 0.0067*** |
| Age 50-60 | 0.1848 | 0.1692 | 0.2181 | -0.0489*** |
| Age 60-70 | 0.0888 | 0.0683 | 0.1302 | -0.0619*** |
| Age>70 | 0.0494 | 0.0252 | 0.0973 | -0.0721*** |
| One Household Member (including head, baseline) | 0.2925 | 0.2451 | 0.4019 | -0.1567*** |
| Two Household Members | 0.2166 | 0.2164 | 0.2151 | 0.0013 |
| Three Household Members | 0.1875 | 0.2052 | 0.1500 | 0.0552*** |
| More than Three Household Members | 0.3034 | 0.3333 | 0.2330 | 0.1002*** |
| *Other Interested Variables* | | | | |
| Adjusted Monthly Income | 1,218 | 1,231 | 1,192 | 39*** |
| Average Moving Distance (in miles) | 24.53 | 24.76 | 23.65 | 1.10 |
| Median Moving Distance (in miles) | 2.77 | 3.00 | 2.14 | 0.86 |
| *N* | 175,556 | 118,001 | 52,463 | |

*Notes:* The table presents the mean value of characteristics for voucher holders in SAFMRs mandatory metropolitan areas in 2017. Demographic control variables for voucher holders are based on the head of the household. Disability status includes whether the household head or any household member is disabled. In Column (2) and (3), the "Black" and "White" category include respondents identified as Hispanic.

## Table 2: Effect of SAFMRs on Voucher Holders' Poverty Exposure

| Dependent Variable | Poverty Rate (0-100) | <20% Poverty (0,1) |
|---|---|---|
| Variable | (1) | (2) |
| (a) SAFMRs Payment Standard | -0.1780*** | 0.0088*** |
| | (0.0201) | (0.0008) |
| Time Fixed Effects | Y | Y |
| County Fixed Effects | Y | Y |
| Household Fixed Effects | Y | Y |
| (b) Move Rate in Mandatory Metros (2017) | 14.54% | 14.54% |
| (c) Treatment-on-Treated ((a)/(b)) | -1.2242*** | 0.0605*** |
| (d) Standardized Effect ((c)/SD) | -0.0990*** | 0.1446*** |
| Avg. Dependent Variable in Mandatory Metros (2017) | 23.1230 | 0.4609 |
| *N* | 2,198,165 | 2,198,165 |

*Notes:* This table reports the estimated effect of SAFMRs payment standard on the surrounding poverty exposure of voucher holders. The treatment variable is a binary indicator equal to one if a household's payment standard is determined by SAFMRs. Column (1) uses census tract poverty rate as the dependent variable; therefore negative coefficients imply poverty reduction. Column (2) uses a binary indicator for tracts with poverty rates below 20 percent; therefore positive coefficients indicate reduced exposure to high-poverty neighborhoods.

**Rows:** (a) Intent-to-Treat (ITT) estimates from Equation 1. All regressions include household, county, and time (contract renewal year–month) fixed effects. Standard errors are clustered at the county–time level and presented in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). (b) Baseline annual move rate in mandated metropolitan areas in 2017, defined as the fraction of voucher holders who moved to a new unit. (c) Treatment-on-the-Treated (TOT) effects, calculated as row (a) divided by row (b). (d) Standardized effects, obtained by dividing row (c) by the standard deviation of the corresponding dependent variable across all census tracts in mandated metropolitan areas.

## Table 3: Effect of SAFMRs on Voucher Holders' Mobility

| Dependent Variable | Moving Address When Renewing Subsidy (0,1) | | |
|---|---|---|---|
| Sample | | Initially Located in | |
| | Overall | Lower Poverty Poverty<20% | Higher Poverty Poverty≥20% |
| Variable | (1) | (2) | (3) |
| (a) SAFMRs Payment Standard | -0.0038** | -0.0059*** | -0.0012 |
| | (0.0017) | (0.0019) | (0.0023) |
| Time Fixed Effects | Y | Y | Y |
| County Fixed Effects | Y | Y | Y |
| Household Control Variables | Y | Y | Y |
| (b) Move Rate in Mandatory Metros (2017) | 14.54% | 13.15% | 15.73% |
| $N$ | 2,198,165 | 889,095 | 1,309,070 |

*Notes:* This table reports the estimated effect of SAFMRs payment standard on the probability of moving for voucher holders. The dependent variable is a binary indicator equal to one if the household has a new address at its annual contract-renewal month. Column (1) pools all households. Column (2) restricts the sample to households whose 2017 census tract had a poverty rate below 20 percent. Column (3) restricts to those starting in tracts with poverty $\geq$ 20 percent.

**Rows:** (a) Intent-to-Treat (ITT) estimates from Equation 1. All regressions include time (contract renewal year–month) fixed effects, county fixed effects, and household-level controls for race/ethnicity, if female household head, presence of children, disability status, age dummies, and household-size dummies as shown in Table 1. Standard errors are clustered at the county–time level and presented in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). (b) Baseline annual move rate in mandated metropolitan areas in 2017, defined as the fraction of voucher holders who moved to a new unit.

**Table 4: Effect of SAFMRs on Voucher Holders' Poverty Exposure, by Household Head Race**

| Dependent Variable | Poverty Rate (0-100) | |
|---|---|---|
| Sample | White | Black |
| Variable | (1) | (2) |
| (a) SAFMRs Payment Standard | -0.2736*** | -0.1145*** |
| | (0.0301) | (0.0247) |
| Time Fixed Effects | Y | Y |
| County Fixed Effects | Y | Y |
| Household Fixed Effects | Y | Y |
| (b) Move Rate in Mandatory Metros (2017) | 11.63% | 16.07% |
| (c) Treatment-on-Treated ((a)/(b)) | -2.3525*** | -0.7125*** |
| (d) Standardized Effects ((c)/SD) | -0.1903*** | -0.0576*** |
| Avg. Dependent Variable in Mandatory Metros (2017) | 20.4037 | 24.4478 |
| *N* | 839,258 | 1,259,224 |

*Notes:* This table reports the estimated effect of SAFMRs payment standard on the surrounding census tract poverty rate of voucher holders. The dependent variable is voucher holders' surrounding census tract poverty rate; therefore negative coefficients imply poverty reduction. The treatment variable is a binary indicator equal to one if a household's payment standard is determined by SAFMRs. Column (1) uses White-headed households and column (2) uses Black-headed households.

**Rows:** (a) Intent-to-Treat (ITT) estimates from Equation 1. All regressions include household, county, and time (contract renewal year–month) fixed effects. Standard errors are clustered at the county–time level and presented in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). (b) Baseline annual move rate in mandated metropolitan areas in 2017, defined as the fraction of voucher holders who moved to a new unit. (c) Treatment-on-the-Treated (TOT) effects, calculated as row (a) divided by row (b). (d) Standardized effects, obtained by dividing row (c) by the standard deviation of the corresponding dependent variable across all census tracts in mandated metropolitan areas.

## Table 5: Effect of SAFMRs on Voucher Holders' Poverty Rate, Interacted with Metropolitan Area Characteristics

| Dependent Variable | Poverty Rate (0-100) | | | | |
|---|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) | (5) |
| SAFMRs Payment Standard | -0.2381 | 0.5005*** | 0.0243 | -0.1746*** | -0.2794*** |
| | (0.2248) | (0.1317) | (0.0986) | (0.0580) | (0.0300) |
| SAFMRs Payment Standard × log(Voucher Count) | 0.0062 | | | | |
| | (0.0226) | | | | |
| SAFMRs Payment Standard × Voucher Concentration | | -0.3822*** | | | |
| | | (0.0736) | | | |
| SAFMRs Payment Standard × Share of High-Rent Units | | | -0.7376** | | |
| | | | (0.3461) | | |
| SAFMRs Payment Standard × Rental Unit Vacancy Rate | | | | -0.0432 | |
| | | | | (0.7260) | |
| SAFMRs Payment Standard × Racial Gap of Voucher Holders in ≥ 20% Poverty | | | | | 0.5696*** |
| | | | | | (0.1181) |
| Avg. Metro-level Interaction Term in Mandatory Metros ($\bar{X}_m$) | 9.1933 | 1.8791 | 0.2880 | 0.0812 | 0.1600 |
| $N$ | 2,198,165 | 2,198,165 | 2,198,165 | 2,198,165 | 2,198,165 |

*Notes:* This table reports the estimated effect of SAFMRs payment standard on the surrounding census tract poverty rate of voucher holders. The dependent variable is the census tract poverty rate; therefore negative coefficients imply poverty reduction. Each reported coefficient is the interaction of the SAFMRs treatment indicator with a metropolitan-level characteristic. Columns (1)–(4) use the four variables HUD used to design mandatory areas of SAFMRs (see Table A1), while column (5) interacts with a 2017 measure of the racial gap of voucher holders in higher poverty neighborhoods—defined as the share of Black voucher holders living in tracts with poverty rates above 20 percent minus the same share for White voucher holders (as presented in Table D2). All regressions include household, county, and time (contract renewal year–month) fixed effects. Standard errors are clustered at the county–time level and presented in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

# Supplement Appendix

Scaling of Small-Area Fair Market Rents
Evidence on Neighborhood Choices of Voucher Recipients

Michael D. Eriksen, Eunjee Kwon, Guoyang Yang

# A Sample Construction and Variable Definitions

## A.1 Sample Construction

We started with a sample of household heads between 2009 to 2020 ($N$=33.33 million) from the PIC data we received. We dropped any voucher holders of home ownership vouchers and project-based vouchers ($N$=0.75 million), and we dropped other programs that are not part of "Section 8 Vouchers" (VO in PIC Database) or "MTW Tenant Based Voucher" (T in MTW PIC Database) ($N$=17.21 million). In addition, we dropped any duplicated household-time observations that some households may be recorded more than once at the same time in different database ($N$=1.12 million). This left us with a sample of 14.25 million observations.

We merged raw PIC data with fair market rent data to identify which households were using SAFMRs as their payment standard (defined as cases where the effective FMR equals the SAFMR), and 1.8% of the sample was without such information and thus was excluded. Then we further restricted the sample to the thirty selected control and treatment metropolitan areas ($N$=5.38 million).

For the poverty rate, we used each census tract poverty rate observed during 2012-2017, since during this period the original data used the 2010 poverty rate consistently. Only 598 observations did not have this measurement; hence we used their first-observed poverty rate as the poverty measure. For household-level demographic control variables, we used their first-observed attributes. Only 888 observations had at least one of the variables missing and thus were excluded. We constructed a repeated cross-section sample at the household level and used the year-month component of the date variable, hereafter referred to as the "effective date", in the PIC data to identify the contract start time when voucher holders were first admitted and the contract renewal time for continuing participation (Collinson and Ganong, 2018). Contract dates before 2014 and after 2019 were also dropped, leaving us with a sample of 3.37 million.

We dropped the voucher households with account type 6 to exclude the effects of house-

holds exit the program (attrition).[ab] This left us with a final sample of 3.19 million observations from 2014 to 2019 because we needed 2014 data to decide if the household moved relative to their previous address. We also dropped voucher holders who do not have 2017 location information (i.e., entered the program after the mandate). We excluded the first observations of each household if coded as "new admission", because their history before admission was unknown (2.5% of the sample), and the remaining observations are used in our analysis. This left us with a sample of 2,198,165 household-month observations from 2015 to 2019.

## A.2 HUD's Mandated Metropolitan Areas Selection Criteria

The four selection benchmarks detailed in columns (1) to (4) of Table A1 are calculated as listed below. We downloaded HUD's selection benchmarks from HUD's website and merged with the rental units vacancy rate from 5-Year American Community Survey (2009-2013). The information for the first three criteria in Table A1 is directly downloaded from HUD (Initial Proposed Selection Tool[c]) In addition, HUD adds an additional criterion (the last vacancy rate requirement) as well as requiring the voucher concentration ratio's numerator for the final rule due to public comments.[d] We calculate each criterion in the following ways:

1. Voucher Count is the total number of voucher households in the metropolitan area.

2. Voucher Concentration in low-income census tracts (census track level measurement aggregate at metropolitan level) is defined as the ratio of vouchers in concentrated-low-income area (CLIA) divided by the number of all vouchers, to the number of renter units in CLIA divided by all renter units. Concentrated low-income areas (CLIAs) are defined as those census tracts in the metropolitan FMRs area with a poverty rate of 25 percent or more, or any tract in the metropolitan FMRs area where at least 50 percent of the households earn less than 60 percent of the area median income adjusted for tract average household size, and that are designated as Qualified Census Tracts (QCTs) for 2016 in accordance with Section 42 of the Internal Revenue Code (26 U.S.C. 42).

3. Share of High-Rent Units is defined as the number of units in area with SAFMRs above 110% Metro FMRs divided by the number of all rental units in that area.

4. Rental Unit Vacancy Rate is defined as the number of vacant units for rent, divided by the sum of vacant rental units, renter-occupied units, and rented-but-unoccupied units..

[a] 1 = new admission (4%), 2 = annual reexamination (64.6%), 3 = interim reexamination (21.4%), 4 = portability move in (vouchers only) (1.1%), 5 = portability move out (vouchers only) (0.2%), 6 = end of participation (5.2%, dropped), 7 = other change of unit (3.3%), 9 = Annual reexamination searching (vouchers only) (0.02%), 13 = annual HQS inspection only (Section 8 only) (0.01%), 14 = historical adjustment (0.13%).

[b] The dropped sample ("end of participation") takes 5.2% overall. The lowest share is in 2019 (4.8%) and the highest is in 2017 (5.5%).

[c] See SAFMRs Proposed Rule Area Selection Tool

[d] See Key Aspects of the Final Rule

We used 5-year estimates from the American Community Survey for 2009 to 2013 from Social Explorer to determine the vacancy rate of rental units at the metropolitan level. Unlike the final rule recommendation,[e] we use 5-year estimates as suggested by HUD. More importantly, 1-year ACS estimates are less representative and cover only a subset of tracts in metropolitan areas.

Though the final rule from HUD also requires the numerator of the third requirement, "voucher concentrated in low-opportunity neighborhoods" above 25% ("The percentage of voucher families living in concentrated low-income areas relative to all renters within the area must be at least 25 percent."), we only use the 155 percent threshold for two main reasons: voucher holders in almost all metropolitan areas are concentrated in high poverty areas (see Figure 1) and initial published proposed selection tool does not include such a requirement.[f] Thus, we combine the three initial selection parameters, together with the rental unit vacancy rate as our parameters when selecting the comparison areas.

## A.3 15 Mandated Metropolitan Areas Used in Our Analysis

Of the 24 metropolitan areas selected by HUD for mandatory SAFMRs adoption in April 2018, 9 were excluded from our analysis for the following reasons.

- First, five HUD metropolitan areas lack observations in our sample: Colorado Springs, CO HUD FMR Metro Area, Urban Honolulu, HI MSA, Palm Bay-Melbourne-Titusville, FL MSA, San Diego-Carlsbad-San Marcos, CA MSA and Tampa-St. Petersburg-Clearwater, FL MSA, as shown in Appendix Figure A2.

- Second, metropolitan areas that adopted SAFMRs before April 2018 and nearby metropolitan areas were also excluded. Chicago-Joliet-Naperville, IL HUD Metro FMR Area, Dallas-Plano-Irving, TX Metro Division, and Fort Worth-Arlington, TX HUD Metro FMR Area were excluded because they have already adopted SAFMRs before April 2018. In addition, five PHAs, Long Beach (CA), Mamaroneck (NY), Cook County (IL), Chattanooga (TN), and Laredo (TX), were also excluded for the same reason.

- Third, any metropolitan areas that opted out of mandatory adoption were excluded, such as those participating in the Move-To-Work (MTW) program that allows housing authority-level administration. The Housing Authority of the City of Pittsburgh (HACP) in Pennsylvania uses a combination of ZIP code and neighborhood-level data, including areas of low voucher use, to define the selected ZIP code areas for the Mobility Voucher Payment Standard: The payment standard for this option is 130 percent of the average of the designated mobility zone SAFMR for the ZIP Codes associated

[e] Vacancy rate is calculated from the 3 most current 1-year ACS estimates and takes average.
[f] See SAFMRs Proposed Rule Area Selection Tool

with the identified areas.[g] In other words, because Pittsburgh only uses two payment standards, we also excluded Pittsburgh, PA HUD Metro FMR Area from the treatment sample.

## A.4 Definition of Neighborhood Poverty Rates

In our analysis, we use the poverty rate variable directly from HUD's original administrative data, aligning with HUD's standards in decision-making to ensure consistency and accuracy. Specifically, we define a time-invariant neighborhood poverty rate as the percentage of the population below the poverty level within a census tract, based on the 2010 Census designation. This approach excludes any spillover effects from voucher recipients on neighborhood poverty; we used the 2010 census tract poverty rate from our 2012-2017 sample, since during this time period the poverty measure is from the 2010 Decennial Census and stays consistent.

## A.5 Definition of Moving

We compare each household's address to its last observed address, and if it is different from the last observed address (sorted by contract renewal time first), we code it as a "moved" household. This means households are only observed when they move *to* a new address upon renewing their subsidy. The "move rate" is calculated as the number of voucher households with any change of address divided by the total number of voucher households in that calendar year, consistent with Collinson and Ganong (2018). When calculating the move rate, households that moved more than once during a calendar year are counted as one to avoid double counting, because our data is recorded at the household-month level.

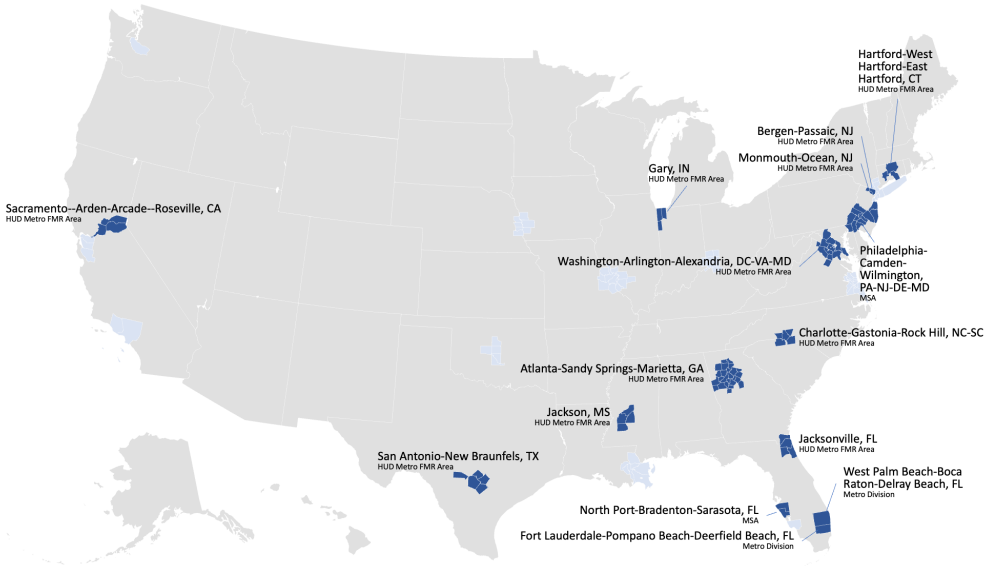
## A.6 Definition of SAFMRs Payment Standard

We compare the household-month-level variable, "effective fair market rent (EFMR)", to the corresponding SAFMR and FMR for that household's location. This payment standard benchmark variable was obtained from the HUD data. If a household's effective fair market rent equals the SAFMR, we define the household as using SAFMRs-based payment standard. Otherwise, households are still using the metropolitan-wide FMRs-based payment standard. This method directly identifies households if they receive the SAFMRs-based voucher on a timely basis accurately, and avoids measurement errors.

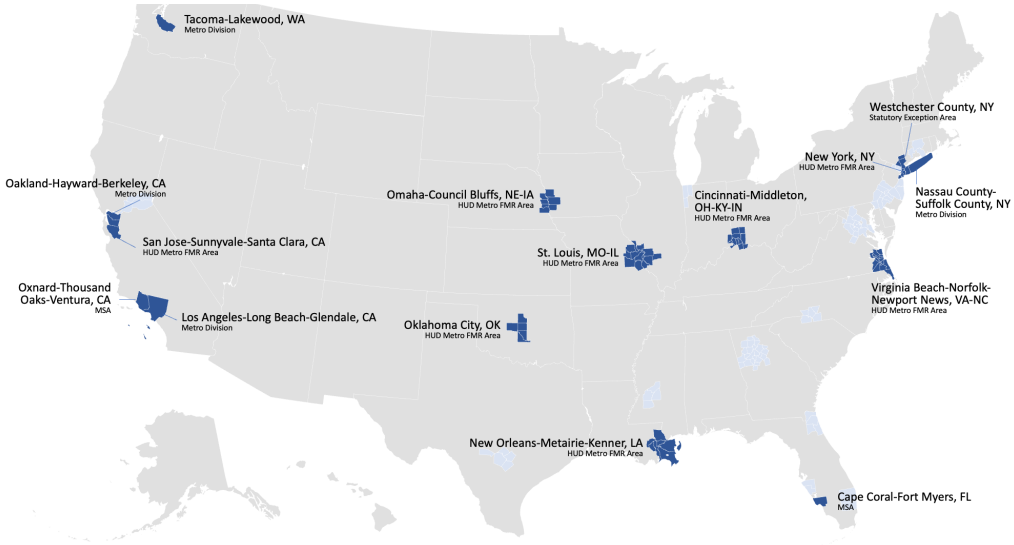
[g] Neighborhoods include Shady Side (15206, 15213, 15232), Lower Lawrenceville (15201, 15213, 15224), Strip District (15201), Southside Flats (15203), Downtown (15219, 15222) and Squirrel Hill (15213, 15217, 15232). See Housing Authority of the City of Pittsburgh 2019 Moving to Work Annual Plan.

## Figure A1: Mandatory and Comparison Metropolitan Areas in the Sample

A. 15 Mandatory Metropolitan Areas

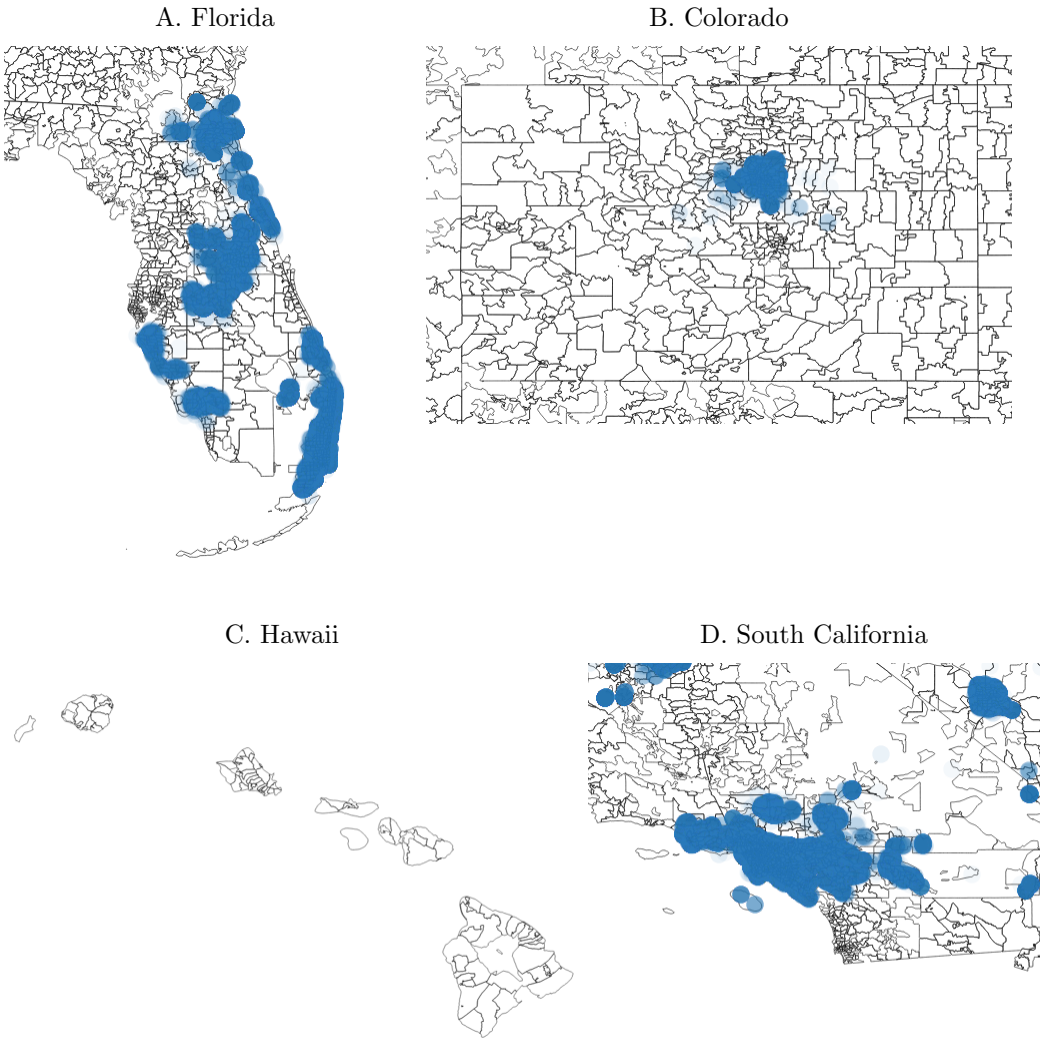



B. 15 Comparison Metropolitan Areas




*Notes:* Panel A displays the 15 mandatory metropolitan areas in our mandatory group sample. Panel B displays the 15 comparison metropolitan areas in our sample of comparison.

**Figure A2: Mandatory Metropolitan Areas with Missing Data**




*Notes:* The blue dots in maps represent the spatial distribution density of all voucher holders in 2017 from the uncleaned raw data we received. Panel A shows the missing observations in Palm Bay-Melbourne-Titusville, FL MSA, and Tampa-St. Petersburg-Clearwater, FL MSA. Panel B shows the missing observations in Colorado Springs, CO HUD FMR Metro Area. Panel C shows the missing observations in Urban Honolulu, HI MSA. Panel D shows the missing observations in San Diego-Carlsbad-San Marcos, CA MSA.

**Table A1: Metropolitan Areas Selected by US Department of Housing and Urban Development for Mandatory SAFMRs Starting in April 2018**

| | Voucher Count | Voucher Concentration | High-Rent Unit | Rental Units Vacancy Rate |
|---|---|---|---|---|
| HUD's Selection Benchmark | $> 2{,}500$ | $> 1.55$ | $> 0.20$ | $> 4\%$ |
| Metros in Mandatory Metro List from HUD | | | | |
| Philadelphia-Camden-Wilmington, PA-NJ-DE-MD MSA | 32,631 | 1.7475 | 0.2555 | 7.54% |
| Washington-Arlington-Alexandria, DC-VA-MD HUD Metro FMR Area | 32,109 | 1.6647 | 0.3139 | 5.25% |
| Atlanta-Sandy Springs-Marietta, GA HUD Metro FMR Area | 28,697 | 1.6074 | 0.2291 | 11.06% |
| San Antonio-New Braunfels, TX HUD Metro FMR Area | 14,633 | 1.9562 | 0.2588 | 8.42% |
| Hartford-West Hartford-East Hartford, CT HUD Metro FMR Area | 12,831 | 1.5969 | 0.2149 | 7.07% |
| Sacramento–Arden-Arcade–Roseville, CA HUD Metro FMR Area | 12,672 | 1.5711 | 0.2837 | 6.55% |
| Bergen-Passaic, NJ HUD Metro FMR Area | 11,503 | 1.5759 | 0.2677 | 5.18% |
| Fort Lauderdale-Pompano Beach-Deerfield Beach, FL Metro Division | 10,486 | 2.1603 | 0.2725 | 9.57% |
| Charlotte-Gastonia-Rock Hill, NC-SC HUD Metro FMR Area | 7,951 | 1.8373 | 0.2505 | 7.16% |
| Monmouth-Ocean, NJ HUD Metro FMR Area | 7,811 | 2.3203 | 0.3516 | 5.15% |
| West Palm Beach-Boca Raton-Delray Beach, FL Metro Division | 6,058 | 1.9970 | 0.4451 | 9.50% |
| Jacksonville, FL HUD Metro FMR Area | 5,872 | 1.9787 | 0.2395 | 10.40% |
| Jackson, MS HUD Metro FMR Area | 4,742 | 1.8480 | 0.3047 | 9.54% |
| Gary, IN HUD Metro FMR Area | 3,305 | 1.7369 | 0.2107 | 6.65% |
| North Port-Bradenton-Sarasota, FL MSA | 2,592 | 2.5878 | 0.2712 | 12.33% |

*Notes:* This table lists the mandated metropolitan areas used in our analysis, originally selected from 24 metropolitan areas by HUD based on four criteria shown in Columns (1) to (4). Column (1) shows the total number of voucher households in each metro. Column (2) measures the rate of concentration of voucher holders in concentrated low-income areas. Column (3) represents the proportion of rental units in areas where the SAFMRs exceed 110% of the metropolitan area FMRs, calculated at the ZIP Code Tabulation Areas (ZCTAs) level. Column (4) details the metropolitan area-level rental vacancy rate, indicating the share of rental units that are vacant, relative to the total number of rental units (occupied and vacant). Of the 24 HUD metropolitan areas that met these criteria, nine were excluded from our analysis due to data inconsistencies or early adoption of SAFMRs. For more information, see Appendix A.

**Table A2: Comparison Metropolitan Areas That Narrowly Missed Selected by US Department of Housing and Urban Development for Mandatory SAFMRs Designation in 2018**

| | Voucher Count | Voucher Concentration | High-Rent Units | Rental Units Vacancy Rate |
|---|---|---|---|---|
| HUD's Selection Benchmark | $> 2{,}500$ | $> 1.55$ | $> 0.20$ | $> 4\%$ |
| **Panel A. Only Change Voucher Count to 2,000 - 2,500** | | | | |
| Cape Coral-Fort Myers, FL MSA | 2,138 | 1.9397 | 0.2464 | 14.70% |
| **Panel B. Only Change Voucher Concentration in Concentrated Low-Income Areas to 1.5 - 1.55** | | | | |
| Los Angeles-Long Beach-Glendale, CA Metro Division | 81,404 | 1.5447 | 0.2738 | 4.43% |
| Cincinnati-Middleton, OH-KY-IN HUD Metro FMR Area | 17,502 | 1.5454 | 0.2193 | 9.23% |
| Westchester County, NY Statutory Exception Area | 10,322 | 1.5288 | 0.3332 | 6.02% |
| **Panel C. Only Change Percent All Units in SAFMR $\geq$ 110% MFMR to 0.18 - 0.20** | | | | |
| New Orleans-Metairie-Kenner, LA HUD Metro FMR Area | 23,316 | 1.7180 | 0.1910 | 10.09% |
| St. Louis, MO-IL HUD Metro FMR Area | 18,297 | 1.7523 | 0.1982 | 7.06% |
| Oklahoma City, OK HUD Metro FMR Area | 11,228 | 1.6280 | 0.1906 | 7.48% |
| Omaha-Council Bluffs, NE-IA HUD Metro FMR Area | 6,391 | 1.6208 | 0.1958 | 7.51% |
| **Panel D. Only Change Rental Unit Vacancy Rate to 3% - 4%** | | | | |
| New York, NY HUD Metro FMR Area | 119,362 | 1.7047 | 0.2092 | 3.78% |
| San Jose-Sunnyvale-Santa Clara, CA HUD Metro FMR Area | 14,307 | 2.1365 | 0.2104 | 3.10% |
| Oxnard-Thousand Oaks-Ventura, CA MSA | 5,612 | 1.5826 | 0.3682 | 3.78% |
| **Panel E. Metros Meet HUD's Standard but Not in Mandatory Metros List** | | | | |
| Oakland-Hayward-Berkeley, CA Metro Division | 28,355 | 1.5523 | 0.2800 | 4.61% |
| Virginia Beach-Norfolk-Newport News, VA-NC HUD Metro FMR Area | 12,291 | 1.6972 | 0.2799 | 7.15% |
| Nassau County-Suffolk County, NY Metro Division | 11,593 | 1.9035 | 0.4834 | 4.73% |
| Tacoma-Lakewood, WA Metro Division | 5,341 | 1.5524 | 0.3367 | 5.81% |

*Notes:* This table shows how the comparison metropolitan areas were selected, with HUD's selection benchmarks detailed in Columns (1)-(4). Column (1) shows the total number of voucher households in each metropolitan area. Column (2) measures the rate of concentration of voucher holders in concentrated low-income areas. Column (3) represents the proportion of rental units in areas where the SAFMRs exceed 110% of the metropolitan-wide FMRs, calculated at the ZIP Code Tabulation Areas (ZCTAs) level. Column (4) details the metropolitan-level rental vacancy rate, indicating the share of rental units that are vacant, relative to total rental units (vacant and renter-occupied). Panels A to D list the comparison metropolitan areas, each relaxing one of the four criteria. Panel E lists four metropolitan areas that originally met HUD's standards but were not selected for HUD's Mandatory Metropolitan Areas list.

# B Alternative Regression Specifications

**Instrumental Variable** To address endogeneity in the use of the SAFMRs payment standard, including voucher holders under different Public Housing Authorities (PHAs) have slower or faster compliance, voucher holders carry vouchers from a mandatory PHA to an non-mandatory PHA, as well as the plausible exogenous timing of the contract starts that recipients only recalibrate the payment standard when they start or renew the leasing contract. We constructed a "leave-one-out" SAFMRs compliance rate using the current month's compliance rate but removed the voucher recipients themselves to exclude any remaining endogeneity concerns (i.e., the same PHA peers compliance rate). Specifically, our first-stage regression in Table B1 is set for households $i$ residing in PHA $p$, counties $c$ (nested in the metropolitan area $m$), in year-month $t$,

$$\mathbb{I}(\text{PayStand=SAFMR})_{ipcmt} = \alpha + \gamma \text{PHA Compliance Rate}_{-i,pcmt} + \lambda_i + \delta_c + \zeta_t + \epsilon_{ipcmt}$$

where an important intuition for constructing the instrument variable is that when voucher holders renew their lease in May 2018, for example, if all their peers who are renewing their lease in May 2018 in the same PHA are using the SAFMRs-based payment standard, they are highly likely to also have the SAFMRs-based payment standard. It is reflected in the significant coefficient of the peer compliance rate that predicts if specific voucher holders use the SAFMRs-based payment standard in that month by the same PHA, as presented in Panel B of Table B1. The determinate of SAFMRs-based payment standards is plausible exogenous and should be decided solely by their administering housing authorities.

**Alternative Control Group** To address concerns that the comparison group drives the treatment effect, we run an additional regression that uses all metropolitan areas in our data as the control group, displayed in Panel A Table B2. In addition, we run a separate regression that uses those metropolitan areas scheduled to adopt SAFMRs in 2025 as the control group, shown in Panel B Table B2.[h]

[h] These metropolitan areas include Akron, OH MSA; Augusta-Richmond County, GA-SC HUD Metro FMR Area; Beaumont-Port Arthur, TX MSA; Birmingham-Hoover, AL HUD Metro FMR Area; Buffalo-Cheektowaga-Niagara Falls, NY MSA; Charleston-North Charleston, SC MSA; Chattanooga, TN-GA MSA; Cincinnati, OH-KY-IN HUD Metro FMR Area; Cleveland-Elyria, OH MSA; Columbus, OH HUD Metro FMR Area; Dayton-Kettering, OH MSA; Des Moines-West Des Moines, IA HUD Metro FMR Area; Detroit-Warren-Livonia, MI HUD Metro FMR Area; Fort Wayne, IN MSA; Greensboro-High Point, NC HUD Metro FMR Area; Harrisburg-Carlisle, PA MSA; Indianapolis-Carmel, IN HUD Metro FMR Area; Jersey City, NJ HUD Metro FMR Area; Kansas City, MO-KS HUD Metro FMR Area; Knoxville, TN HUD Metro FMR Area; Los Angeles-Long Beach-Glendale, CA HUD Metro FMR Area; Louisville, KY-IN HUD Metro FMR Area; Memphis, TN-MS-AR HUD Metro FMR Area; Miami-Miami Beach-Kendall, FL HUD Metro FMR Area; Mobile, AL HUD Metro FMR Area; Montgomery, AL MSA; Nashville-Davidson–Murfreesboro–Franklin, TN HUD Metro FMR Area; Oklahoma City, OK HUD Metro FMR Area; Omaha-Council Bluffs, NE-IA HUD Metro FMR Area; Orlando-Kissimmee-Sanford, FL MSA; Oxnard-Thousand Oaks-Ventura, CA MSA; Phoenix-Mesa-Scottsdale, AZ MSA; Raleigh, NC MSA; San Jose-Sunnyvale-Santa Clara, CA HUD Metro FMR Area; Seattle-Bellevue, WA HUD Metro FMR Area; St. Louis, MO-IL HUD Metro FMR Area; Tucson, AZ MSA; Tulsa, OK HUD Metro FMR Area; Virginia Beach-Norfolk-Newport News, VA-NC HUD Metro FMR Area; Wichita, KS HUD Metro FMR Area; Winston-Salem, NC HUD Metro FMR Area

## Table B1: Effect of SAFMRs on Voucher Holders' Poverty Exposure

Panel A: IV Regression

| Dependent Variable | Poverty Rate (0-100) | <20% Poverty (0,1) |
|---|---|---|
| Variable | (1) | (2) |
| (a) SAFMRs Payment Standard | -0.1744*** | 0.0087*** |
| | (0.0200) | (0.0008) |
| Time Fixed Effects | Y | Y |
| County Fixed Effects | Y | Y |
| Household Fixed Effects | Y | Y |
| (b) Move Rate in Mandatory Metros (2017) | 14.54% | 14.54% |
| (c) Treatment-on-Treated ((a)/(b)) | -1.1994*** | 0.0598*** |
| (d) Standardized Effect ((c)/SD) | -0.0970*** | 0.1429*** |
| Avg. Dependent Variable in Mandatory Metros (2017) | 23.1230 | 0.4609 |
| $N$ | 2,198,165 | 2,198,165 |

Panel B: First-Stage IV Regression

| Dependent Variable | SAFMRs Payment Standard |
|---|---|
| Variable | (1) |
| $1^{st}$ Stage: PHA Compliance Rate$_{-i,pcmt}$ | 0.9865*** |
| | (0.0004) |
| $1^{st}$ Stage K-P Wald rk F statistic | 7,533,297 |
| $N$ | 2,198,165 |

*Notes:* The table reports the estimated effect of SAFMRs payment standard on the surrounding census tract poverty exposure of voucher holders. The independent variable is a binary indicator of whether households' payment standards are determined by SAFMRs. Columns (1) uses census tract poverty rate as the dependent variable; Columns (2) uses a binary indicator for tracts with poverty rates below 20 percent. The results present 2SLS (Two-Stage Least Squares) results with leave-one-out SAFMRs compliance rate of the PHA administering their voucher as an instrument, where first stage regression result is shown in Panel B.
**Rows:** (a) Intent-to-Treat (ITT) estimates from Equation 1. All regressions include household, county, and (contract renewal year-month) fixed effects. Standard errors are clustered at the county–time level and presented in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). (b) Baseline annual move rate in mandated metropolitan areas in 2017. Defined as the fraction of voucher holders who moved to a new unit. (c) Treatment-on-the-Treated (TOT) effects, calculated as row (a) divided by row (b). (d) Standardized effects, obtained by dividing row (c) by the standard deviation of the corresponding dependent variable across all census tracts in mandated metropolitan areas.

## Table B2: Effect of SAFMRs on Voucher Holders' Poverty Exposure: Alternative Comparison Metropolitan Areas

Panel A: All Available Metropolitan Areas as Comparison Group

| Dependent Variable | Poverty Rate (0-100) | <20% Poverty (0,1) |
|---|---|---|
| Variable | (1) | (2) |
| (a) SAFMRs Payment Standard | -0.1320*** | 0.0065*** |
| | (0.0187) | (0.0007) |
| (b) Move Rate in Mandatory Metros (2017) | 14.54% | 14.54% |
| (c) Treatment-on-Treated | -0.9078*** | 0.0447*** |
| (d) Standardized Effect | -0.0734*** | 0.1068*** |
| Avg. DV in Mandatory Metros (2017) | 23.1230 | 0.4609 |
| *N* | 4,955,022 | 4,955,022 |

Panel B: 2025 Mandatory Metropolitan Areas as Comparison Group

| Dependent Variable | Poverty Rate (0-100) | <20% Poverty (0,1) |
|---|---|---|
| Variable | (1) | (2) |
| (a) SAFMRs Payment Standard | -0.1396*** | 0.0074*** |
| | (0.0205) | (0.0008) |
| (b) Move Rate in Mandatory Metros (2017) | 14.54% | 14.54% |
| (c) Treatment-on-Treated | -0.9601*** | 0.0509*** |
| (d) Standardized Effect | -0.0776*** | 0.1216*** |
| Avg. DV in Mandatory Metros (2017) | 23.1230 | 0.4609 |
| *N* | 2,385,473 | 2,385,473 |

*Notes:* The table reports the estimated effect of SAFMRs payment standard on surrounding census tract poverty exposure of voucher holders, using alternative comparison metropolitan areas. Panel A uses all available metropolitan areas as our control groups, and Panel B uses 2025 SAFMRs mandatory metropolitan areas as our control groups. The independent variable is a binary indicator of whether households' payment standards are determined by SAFMRs. Columns (1) uses census tract poverty rate as the dependent variable; Columns (2) uses a binary indicator for tracts with poverty rates below 20 percent.

**Rows:** (a) Intent-to-Treat (ITT) estimates from Equation 1. All regressions include household, county, and time (contract-renewal year-month) fixed effects. Standard errors are clustered at the county–time level and presented in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). (b) Baseline annual move rate in mandated metropolitan areas in 2017. Defined as the fraction of voucher holders that moved to a new unit. (c) Treatment-on-the-Treated (TOT) effects, calculated as row (a) divided by row (b). (d) Standardized effects, obtained by dividing row (c) by the standard deviation of the corresponding dependent variable across all census tracts in mandated metropolitan areas.

# C Comparison with the 2011 Dallas Demonstration

We benchmark our standardized estimates for the 2018 mandate against those from the 2011 Dallas experiment analyzed by Collinson and Ganong (2018). Specifically, we apply two identification strategies: (1) the difference-in-differences method used by Collinson and Ganong (2018), and (2) our own identification approach outlined in Section 3.3.

**Collinson and Ganong (2018) Method** Table C1 (Panel A) presents their results (Table 4 in Collinson and Ganong (2018)), comparing the results before (2010) and after (2013) the implementation of SAFMRs in Dallas (treatment) and Fort Worth (control). The authors used a difference-in-differences design without control variables, clustering standard errors at the census tract level, to identify the impact of SAFMRs on the average poverty reduction. Their identification assumption is that two years after the implementation of the SAFMRs, all voucher holders' payment standards in those areas are affected by SAFMRs. Their overall intent-to-treat (ITT) estimate (column (7)) includes both movers and non-movers. Their treatment-on-treated (TOT) (column (8)) estimate is obtained by dividing the ITT by the fraction of movers. The standardized effect, which divides the TOT by the standard deviation of the poverty rates of all census tracts in Dallas (column (9)), is -0.188.

To facilitate a direct comparison, we replicate this methodology using our sample of mandated metropolitan areas (treatment) and their respective comparison metropolitan areas, focusing on the period before (2017) and after (2019) the implementation of SAFMRs. Panel B of Table C1 presents these results, where column (7) reports the ITT estimates (with clustered standard errors at the tract level), column (8) provides the TOT estimates (the ITT divided by the fraction of movers), and column (9) displays the standardized effect (the TOT divided by the standard deviation of the census tracts in the treatment area). Although the results indicate a poverty-reducing effect, the magnitude of the standardized effect (-0.0767) is noticeably smaller than in the 2011 Dallas case.

**Our Identification Strategy** Next, we apply our identification strategy from Section 3.3 to the Dallas sample of 2009-2013. Figure 5 (with point estimates presented in Panel A and Panel B of Table D5) reports these estimates. Compared to the results in Table C1, our empirical approach yields slightly larger estimates than the method used by Collinson and Ganong (2018) for both the Dallas 2011 expansion and the 2018 mandated metropolitan areas. This difference arises because our approach specifically identifies households that actually transition to SAFMRs payment standards, whereas the method in Table C1 averages over all voucher holders in the treatment and comparison areas. Our approach also controls for time-invariant unobserved household characteristics (household fixed effect), as well as time and location fixed effects. Despite these differences, consistent with the Appendix Table C1, we also find a larger standardized effect in the 2011 Dallas sample than in the 2018 mandated metro sample. In Section 5, we demonstrate that the muted results for the 2018 phase primarily stem from substantial heterogeneity among the metropolitan areas mandated in 2018.

## Table C1: Comparing SAFMRs Impacts: 2011 Dallas vs. 2018 Mandate

Panel A. 2011 Dallas Experiment (Table 4 in Collinson and Ganong (2018))

| | Fort Worth (control) | | Dallas (treatment) | | Differences | | Diff-in-Diff (ITT) | Diff-in-Diff (TOT) | Standardized effect |
|---|---|---|---|---|---|---|---|---|---|
| | Pre (1) | Post (2) | Pre (3) | Post (4) | (2)-(1) (5) | (4)-(3) (6) | (6)-(5) (7) | (8) | (8)/SD (9) |
| Estimates *2013 vs. 2010* | 0.174 | 0.172 | 0.210 | 0.199 | -0.001 | -0.011 | -0.009 (0.003) | -0.021 | -0.188 |
| Observations | 7,203 | 7,038 | 19,315 | 19,399 | | | | | |
| n moved (2013 vs. 2010) | | 3,041 | | 8,899 | | | | | |
| Implied move rate | | 42% | | 46% | | | | | |

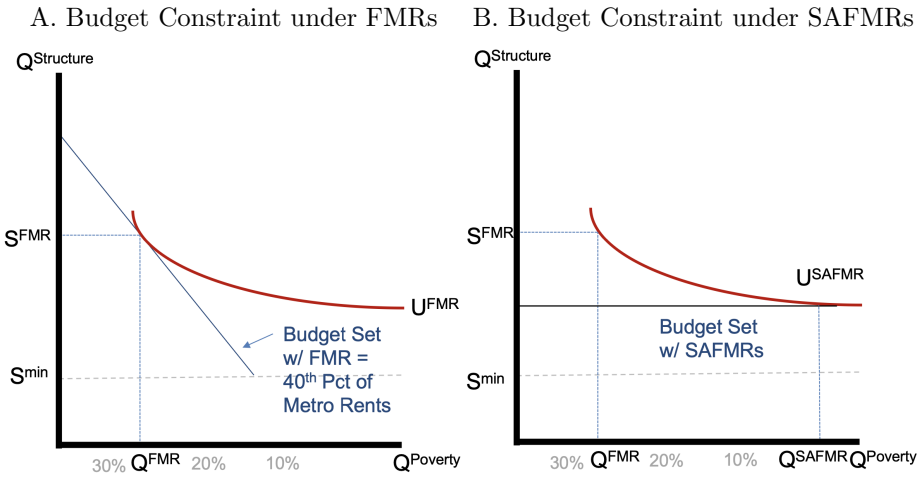
Panel B. 2018 Mandate

| | Comparison metropolitan areas (control) | | Mandatory metropolitan areas (treatment) | | Differences | | Diff-in-Diff (ITT) | Diff-in-Diff (TOT) | Standardized effect |
|---|---|---|---|---|---|---|---|---|---|
| | Pre | Post | Pre | Post | (2)-(1) | (4)-(3) | (6)-(5) | | (8)/SD |
| Estimates *2019 vs. 2017* | 0.2591 | 0.2600 | 0.2316 | 0.2306 | 0.0009 | -0.0009 | -0.0018 (0.0009) | -0.0095 | -0.0767 |
| Observations | 336,797 | 326,268 | 178,034 | 182,081 | | | | | |
| n moved (2019 vs. 2017) | | 41,188 | | 33,335 | | | | | |
| Implied move rate | | 12.23% | | 18.23% | | | | | |

*Notes*: This table presents the estimates effect of transitioning from FMRs to SAFMRs on voucher holders' neighborhood poverty rate. The dependent variable is census tract poverty rate; therefore negative coefficients imply poverty reduction. Panel A reports results from the 2011 Dallas experiment (Table 4 in Collinson and Ganong (2018)), covering the period from 2010 to 2013, with Dallas as the treatment group and Fort Worth as the control group. Panel B applies the Collinson and Ganong (2018) methodology to our 2018 mandated metro samples (comparing 2019 to 2017), using these mandated metropolitan areas as the treatment group and the comparison group described in Section A. Column (7) shows the Intent-to-Treat (ITT) estimates, with standard errors for the difference-in-differences estimate reported in parentheses (clustered at the tract level). Column (8) presents the Treatment-on-Treated (TOT) estimates, calculated by dividing the ITT estimates (column (7)) by the fraction of tenants who moved to a new unit. Column (9) provides standardized effects, where each difference-in-differences estimate is divided by the standard deviation across all census tracts in the treatment areas. Panel A's move rate is calculated as the number of households who changed ZIP code between 2010 and 2013 in treatment areas, divided by the total number of households in the pre-treatment period (2010). Panel B uses the same approach, though we define a move more strictly as one that involves a change of address and requires non-missing addresses in our data.

# D Auxillary Tables

**Figure D1: Conceptual Framework: Households' Choices under FMRs versus SAFMRs**




*Notes*: The horizontal axis represents neighborhood quality, while the vertical axis represents structure (housing unit) quality, with higher values indicating better quality. The straight lines illustrate the budget constraints under different voucher payment standard, and the utility indifference curves for voucher holders are also depicted. $S_{\min}$ on the y-axis denotes the minimum structure quality requirement for voucher holders as set by HUD. Panel A illustrates budget sets under the FMR system, which provides the same rental subsidy across an entire metropolitan area. Under this system, households with vouchers face a downward-sloping budget constraint, leading to a trade-off between neighborhood and unit quality within a fixed budget. Panel B represents the budget sets under the SAFMRs system, where the payment standard increases with neighborhood quality. Under this system, HUD also requires a minimum unit quality to be maintained. Compared to the FMR system, SAFMRs aims to improve neighborhood quality from $Q_{\text{FMR}}$ to $Q_{\text{SAFMR}}$ while ensuring a minimum structure (unit) quality standard is met.

**Table D1: Descriptive Statistics for Voucher Holders in SAFMRs Mandatory Metropolitan Areas, 2017**

| 2017 Value (Mean) | (1) Continuing Recipients | (2) First-Time Recipients | (3) Difference b/w (1) and (2) |
|---|---|---|---|
| *Dependent Variables* | | | |
| Census Tract Poverty Rate | 23.1230 | 24.1052 | -0.9822*** |
| <20% Poverty Tract | 0.4609 | 0.4376 | 0.0233*** |
| *Voucher Holders Demographics* | | | |
| Black | 0.6722 | 0.6182 | 0.0539*** |
| Asian | 0.0192 | 0.0100 | 0.0092*** |
| Other Race | 0.0098 | 0.0144 | -0.0045*** |
| Hispanic | 0.1546 | 0.1738 | -0.0192*** |
| Female | 0.8465 | 0.7032 | 0.1433*** |
| Kids Present | 0.5850 | 0.4743 | 0.1107*** |
| Household Member w/ Disabilities | 0.2496 | 0.2755 | -0.0259*** |
| Age≤30 (Baseline) | 0.1866 | 0.2281 | -0.0415*** |
| Age 30-40 | 0.2759 | 0.2420 | 0.0339*** |
| Age 40-50 | 0.2145 | 0.1377 | 0.0769*** |
| Age 50-60 | 0.1848 | 0.1998 | -0.0150*** |
| Age 60-70 | 0.0888 | 0.1300 | -0.0412*** |
| Age>70 | 0.0494 | 0.0625 | -0.0131*** |
| One Household Member (including head, baseline) | 0.2925 | 0.4168 | -0.1243*** |
| Two Household Members | 0.2166 | 0.2062 | 0.0105*** |
| Three Household Members | 0.1875 | 0.1458 | 0.0416*** |
| More than Three Household Members | 0.3034 | 0.2312 | 0.0722*** |
| *N* | 175,556 | 6,116 | |

*Notes:* The table presents the mean value of characteristics for voucher holders in SAFMRs mandatory metropolitan areas in 2017. Demographic control variables for voucher holders are based if newly admitted with voucher or renewed at least once. Disability status includes whether the household head or any household member is disabled.

## Table D2: Percentage of Voucher Holders in High Poverty Areas

| Sample: Mandatory Metropolitan Areas in 2017 | (1) % of **all** VH in Poverty ≥ 20% | (2) % of **Black** VH in Poverty ≥ 20% | (3) % of **White** VH in Poverty ≥ 20% | (4) Gap (ppt) (2)–(3) |
|---|---|---|---|---|
| Overall | 53.91 | 58.76 | 43.47 | 15.29*** |
| Atlanta-Sandy Springs-Marietta, GA HUD Metro FMR Area | 67.02 | 67.63 | 52.36 | 15.27*** |
| Bergen-Passaic, NJ HUD Metro FMR Area | 38.19 | 53.49 | 31.72 | 21.77*** |
| Charlotte-Gastonia-Rock Hill, NC-SC HUD Metro FMR Area | 64.85 | 66.24 | 54.16 | 12.08*** |
| Fort Lauderdale-Pompano Beach-Deerfield Beach, FL Metro Division | 68.06 | 73.07 | 46.47 | 26.60*** |
| Gary, IN HUD Metro FMR Area | 71.97 | 74.97 | 54.24 | 20.73*** |
| Hartford-West Hartford-East Hartford, CT HUD Metro FMR Area | 56.76 | 57.11 | 56.71 | 0.41 |
| Jackson, MS HUD Metro FMR Area | 79.89 | 80.59 | 47.83 | 32.76*** |
| Jacksonville, FL HUD Metro FMR Area | 62.07 | 64.72 | 45.78 | 18.94*** |
| Monmouth-Ocean, NJ HUD Metro FMR Area | 40.11 | 32.27 | 44.54 | –12.27*** |
| North Port-Bradenton-Sarasota, FL MSA | 48.82 | 58.01 | 33.94 | 24.07*** |
| Philadelphia-Camden-Wilmington, PA-NJ-DE-MD MSA | 54.37 | 64.51 | 27.16 | 37.35*** |
| Sacramento–Arden-Arcade–Roseville, CA HUD Metro FMR Area | 62.74 | 70.43 | 53.11 | 17.32*** |
| San Antonio-New Braunfels, TX HUD Metro FMR Area | 68.65 | 64.04 | 70.07 | –6.03*** |
| Washington-Arlington-Alexandria, DC-VA-MD HUD Metro FMR Area | 24.23 | 27.90 | 9.06 | 18.84*** |
| West Palm Beach-Boca Raton-Delray Beach, FL Metro Division | 68.14 | 71.11 | 58.96 | 12.15*** |

*Notes*: The table reports, for each SAFMR-mandated metropolitan area in 2017, the share of voucher holders (VH) living in high-poverty census tracts (poverty rate ≥ 20 percent). Columns (2) and (3) present the excess concentration of Black-headed and White-headed voucher households in high-poverty census tracts, respectively, defined as: (% of Black or White VH in ≥ 20 percent poverty tracts) − (overall % of VH in ≥ 20 percent poverty tracts in the same metro (column (1)).

## Table D3: Effect of SAFMRs on Voucher Holders' Mobility by Race

| Dependent Variable | Moving Address When Renewing Subsidy (0,1) | | | |
|---|---|---|---|---|
| | Initially Located in | | | |
| Sample | Lower Poverty Poverty<20% | | Higher Poverty Poverty≥20% | |
| | Black | White | Black | White |
| Variable | (1) | (2) | (3) | (4) |
| (a) SAFMRs Payment Standard | -0.0074*** | -0.0029 | -0.0005 | -0.0030 |
| | (0.0027) | (0.0022) | (0.0027) | (0.0029) |
| Time Fixed Effects | Y | Y | Y | Y |
| County Fixed Effects | Y | Y | Y | Y |
| Household Control Variables | Y | Y | Y | Y |
| Avg. DV in Mandatory Metros (2017) | 0.1510 | 0.0998 | 0.1631 | 0.1356 |
| *N* | 450,806 | 385,739 | 808,414 | 453,515 |

*Notes:* This table reports the estimated effect of SAFMRs payment standard on probability of moving of voucher holders, by household head race. The dependent variable is an binary indicator equal to one if the household has a new address at its annual contract renewal month. Sub-samples are divided based on the poverty rate of the voucher holders' initial locations in 2017: Column (1) and (2) focuses on the tracts with poverty rates below 20%; Column (3) and (4) focuses on the tracts with poverty rates above 20%.
**Rows:** (a) Intent-to-Treat (ITT) estimates from Equation 1. All regressions include time (contract renewal year–month) fixed effects, county fixed effects, and household-level controls for race/ethnicity, female headship, presence of children, disability status, age dummies, and household-size dummies as shown in Table 1. Standard errors are clustered at the county–time level and presented in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).*** $p < 0.01$).

**Table D4: Effect of SAFMRs on Voucher Holders' Poverty Rate by Household Head Race and If School Age Kids Present**

| Sample | | | Black | | White | |
|---|---|---|---|---|---|---|
| Dependent Variable: Poverty Rate (0-100) | w/o School Age Kids | w/ School Age Kids | w/o School Age Kids | w/ School Age Kids | w/o School Age Kids | w/ School Age Kids |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| (a) SAFMRs Payment Standard | -0.1494*** | -0.1785*** | -0.0831*** | -0.1181*** | -0.2395*** | -0.3327*** |
| | (0.0215) | (0.0330) | (0.0270) | (0.0407) | (0.0319) | (0.0526) |
| Time Fixed Effects | Y | Y | Y | Y | Y | Y |
| County Fixed Effects | Y | Y | Y | Y | Y | Y |
| Household Fixed Effects | Y | Y | Y | Y | Y | Y |
| (b) Move Rate in Mandatory Metros (2017) | 12.73% | 17.88% | 10.30% | 15.34% | 14.27% | 18.85% |
| (c) Treatment-on-Treated ((a)/(b)) | -1.1736*** | -0.9983*** | -0.8068*** | -0.7699*** | -1.6783*** | -1.7650*** |
| (d) Standardized Effect ((c)/SD) | -0.0949*** | -0.0807*** | -0.0652*** | -0.0623*** | -0.1357*** | -0.1427*** |
| Avg. DV in Mandatory Metros (2017) | 23.0090 | 23.3325 | 25.0381 | 23.5427 | 19.5200 | 22.8601 |
| *N* | 1,543,012 | 655,153 | 819,584 | 439,640 | 643,998 | 195,260 |

*Notes:* This table reports the estimated effect effect of SAFMRs payment standard on surrounding census tract poverty rate of voucher holders, by household head race, and whether any school age kids (6-12) present in the households when they first appeared in the sample. The dependent variable is the census tract poverty rate; therefore, negative coefficients imply poverty reduction. School-age children are between the ages of 6-12. The independent variable is a binary indicator of whether households' payment standards are determined by SAFMRs. Column (1) shows the overall results with and without school-age kids, columns (3) and (4) show the results of Black, and columns (5) and (6) show the results of White-headed households.

**Rows:** (a) Intent-to-Treat (ITT) estimates from Equation 1. All regressions include household, county, and time (contract-renewal year–month) fixed effects. Standard errors are clustered at the county-time level and are presented in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). (b) Baseline annual move rate in mandated metropolitan areas in 2017. Defined as the fraction of voucher holders who moved to a new unit. (c) Treatment-on-the-Treated (TOT) effects, calculated as row (a) divided by row (b). (d) Standardized effects, obtained by dividing row (c) by the standard deviation of the corresponding dependent variable across all census tracts in mandated metropolitan areas.

## Table D5: Effect of SAFMRs on Surrounding Tract Poverty Rate across Metropolitan Areas

| | Dependent Variable: Poverty Rate (0-100) | | | | |
|---|---|---|---|---|---|
| | Intent-to-Treat (ITT) | Move Rate | Treat-on-Treated (TOT) (1)/(2) | Standardized effect (3)/SD | Significance level |
| Demonstration Site or Metropolitan Areas | (1) | (2) | (3) | (4) | (5) |
| **Panel A. Housing Authority of the City of Dallas** | | | | | |
| (2009-2013) | -0.5712 | 19.66% | -2.9055 | -0.2304 | *** |
| **Panel B. 2018 Metropolitan Areas** | | | | | |
| Overall (2015-2019) | -0.1780 | 14.54% | -1.2245 | -0.0990 | *** |
| **Panel C. 2018 Mandatory Metropolitan Areas Heterogeneity** | | | | | |
| Atlanta-Sandy Springs-Marietta, GA HUD Metro FMR Area | -0.1193 | 15.61% | -0.7641 | -0.0614 | *** |
| Bergen-Passaic, NJ HUD Metro FMR Area | 0.1018 | 8.35% | 1.2195 | 0.1042 | *** |
| Charlotte-Gastonia-Rock Hill, NC-SC HUD Metro FMR Area | 0.2215 | 12.87% | 1.7209 | 0.1401 | *** |
| Fort Lauderdale-Pompano Beach-Deerfield Beach, FL Metro Division | -0.3572 | 22.30% | -1.6020 | -0.1597 | *** |
| Gary, IN HUD Metro FMR Area | -0.2772 | 12.05% | -2.3003 | -0.1408 | *** |
| Hartford-West Hartford-East Hartford, CT HUD Metro FMR Area | -0.4720 | 14.78% | -3.1936 | -0.2193 | *** |
| Jackson, MS HUD Metro FMR Area | -0.4942 | 13.68% | -3.6120 | -0.2367 | *** |
| Jacksonville, FL HUD Metro FMR Area | 0.3848 | 17.68% | 2.1761 | 0.1891 | *** |
| Monmouth-Ocean, NJ HUD Metro FMR Area | -0.4657 | 10.04% | -4.6388 | -0.5422 | *** |
| North Port-Bradenton-Sarasota, FL MSA | -0.4725 | 13.58% | -3.4792 | -0.3648 | *** |
| Philadelphia-Camden-Wilmington, PA-NJ-DE-MD MSA | -0.1646 | 13.86% | -1.1879 | -0.0869 | *** |
| Sacramento–Arden-Arcade–Roseville, CA HUD Metro FMR Area | 0.2882 | 8.83% | 3.2649 | 0.2844 | *** |
| San Antonio-New Braunfels, TX HUD Metro FMR Area | -0.5251 | 23.81% | -2.2057 | -0.1700 | *** |
| Washington-Arlington-Alexandria, DC-VA-MD HUD Metro FMR Area | -0.2337 | 13.05% | -1.7903 | -0.2027 | *** |
| West Palm Beach-Boca Raton-Delray Beach, FL Metro Division | -0.2688 | 19.15% | -1.4038 | -0.1259 | *** |

*Notes*: The table displays heterogeneity estimated effects of existing voucher holders by Dallas public housing authority before the 2018 mandatory, and each SAFMRs mandatory metropolitan area (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). The dependent variable is census-tract poverty rate; therefore negative coefficients imply poverty reduction. The control group for Dallas is PHAs with similar attributes including FMR level, number of vouchers, working age population and exactly matched the control groups in Dastrup et al. (2018). Significance levels are indicated by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Comparison metropolitan areas, effect definitions, and the TOT vs. ITT framework remain as described in the main text.

## Table D6: Effect of SAFMRs on Surrounding Tract Poverty Rate across Metropolitan Areas by Race

| Dependent Variable: Poverty Rate (0-100) | N (2017) | % Black | Black | | White | |
|---|---|---|---|---|---|---|
| 2018 Mandatory Metropolitan Areas | (1) | (2) | (3) Standardized Effect | (4) Significance | (5) Standardized Effect | (6) Significance |
| **2015–2019** | | | | | | |
| Overall | 175,556 | 67.22% | -0.0576 | *** | -0.1903 | *** |
| Atlanta-Sandy Springs-Marietta, GA HUD Metro FMR Area | 26,758 | 93.87% | -0.0332 | * | -0.1779 | * |
| Bergen-Passaic, NJ HUD Metro FMR Area | 10,646 | 32.03% | 0.2804 | *** | -0.0636 | |
| Charlotte–Gastonia–Rock Hill, NC–SC | 5,721 | 87.85% | 0.1357 | *** | 0.5418 | *** |
| Fort Lauderdale-Pompano Beach-Deerfield Beach, FL Metro Division | 10,720 | 80.58% | -0.1194 | *** | -0.2976 | *** |
| Gary, IN HUD Metro FMR Area | 3,375 | 85.13% | -0.0679 | | -0.4543 | *** |
| Hartford-West Hartford-East Hartford, CT HUD Metro FMR Area | 12,881 | 31.01% | -0.1536 | *** | -0.2755 | *** |
| Jackson, MS HUD Metro FMR Area | 4,609 | 97.57% | -0.2107 | *** | 0.0593 | |
| Jacksonville, FL | 6,897 | 85.69% | 0.2212 | *** | 0.0854 | |
| Monmouth-Ocean, NJ HUD Metro FMR Area | 7,727 | 34.05% | -0.3450 | *** | -0.7609 | *** |
| North Port-Bradenton-Sarasota, FL MSA | 2,538 | 62.02% | -0.3963 | *** | -0.2503 | * |
| Philadelphia-Camden-Wilmington, PA-NJ-DE-MD MSA | 28,520 | 71.55% | -0.0657 | *** | -0.1107 | *** |
| Sacramento–Arden–Arcade–Roseville, CA | 10,497 | 43.62% | 0.3547 | *** | 0.1836 | ** |
| San Antonio-New Braunfels, TX HUD Metro FMR Area | 9,230 | 24.01% | -0.2105 | *** | -0.1832 | *** |
| Washington-Arlington-Alexandria, DC-VA-MD HUD Metro FMR Area | 29,542 | 77.22% | -0.1742 | *** | -0.1866 | *** |
| West Palm Beach-Boca Raton-Delray Beach, FL Metro Division | 5,895 | 73.21% | -0.0811 | | -0.1803 | *** |

*Notes*: This table reports the heterogeneity in policy effectiveness across metropolitan areas by household head race. Column (1) reports the number of voucher holders. Column (2) is the percentage of those voucher holders who are Black. Columns (3)-(4) show the standardized effects and significance level for Black-headed voucher holders; Columns (5)-(6) do the same for White-headed voucher holders. A negative standardized effect indicates an improvement (i.e., a reduction in the poverty rate). Significance levels are indicated by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Definitions of comparison metropolitan areas, effect measures, and the TOT vs. ITT framework are the same as described in the main text.