Horizontal Scaling of Small-Area Fair Market Rents (SAFMR): Effects on Housing Voucher Location Choices*

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Abstract

This paper examines the scalability of the Small Area Fair Market Rent (SAFMR) policy—a reform of the Housing Choice Voucher (HCV) program that adjusts subsidy caps based on ZIP code–level rents. Initially piloted in the Dallas metropolitan area in 2011, SAFMR enabled voucher recipients to move to lower-poverty neighborhoods, reducing their exposure to poverty. Drawing on HUD administrative data on 270,000 voucher holders from 2015 to 2019, we evaluate the broader applicability of the 2018 SAFMR mandate across 15 metropolitan areas. Our findings show reduced poverty exposure among movers but unchanged overall mobility rates. White households are twice as likely as others to relocate to lower-poverty areas, reflecting ongoing mobility challenges for minority voucher recipients. Substantial variation in policy effectiveness across metros underscores the importance of local context in scaling housing interventions. These results highlight the need to address barriers facing low-income households and emphasize the importance of careful policy design for replicating small-scale successes across diverse settings.

Keywords: Housing Voucher, Mobility, Small Area Fair Market Rent, Fair Market Rent

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1 Introduction

The significance of residential environments for the well-being of families is well documented in the prior literature (Chetty, Hendren, and Katz, 2016; Aliprantis and Richter, 2020; Chyn and Katz, 2021), with more recent studies highlighting the advantages of residing in lower-poverty areas for the development of children and their lifetime earnings (e.g., Ludwig et al., 2013; Chetty, Hendren, and Katz, 2016; Chetty and Hendren, 2018; Chyn, 2018). However, an increasing percentage of low-income households that receive housing subsidies reside in high-poverty neighborhoods, despite more than $60 billion in annual federal expenditures (Pollakowski et al., 2022; Ellen, O'Regan, and Harwood, 2023). Therefore, aiming to improve access to lower-poverty neighborhoods and improve the life outcomes of children of Housing Choice Voucher (HCV) recipients has become a key policy target. [1]. In this paper, we examine the scalability of indexing maximum recipient rents under the HCV program to Zip codes to reduce surrounding neighborhood poverty rates of receipients.

The HCV program previously relied on a single metropolitan-wide subsidy cap known as the Fair Market Rent (FMR), determined annually by the U.S. Department of Housing and Urban Development (HUD). The FMR was established at 40% of the asking rents in a recipient's metropolitan area, with the recipients contributing 30% of their gross income directly to their landlords. This system unintentionally created a trade-off for voucher recipients to use the subsidy to improve their consumption of physical housing quality or neighborhood amenities(Susin, 2002; Eriksen and Ross, 2015; Ellen, 2020). This incentive structure and the well-documented high search costs of low-income families resulted in the majority of recipients residing in their same neighborhoods after entering the program.

Following a court settlement and the acknowledged persistence in segregation patterns of the above incentives, HUD first allowed alternative voucher subsidy caps based on the rental distribution of individual ZIP codes within Dallas starting in 2011 (Collinson and Ganong,

[1]The persistence of housing voucher recipients in high-poverty neighborhoods has been explained in the prior literature by a combination of uncertain private benefits for recipients (Dastrup, Finkel, and Ellen, 2019; Bergman et al., 2024a), myopic behavior of parents, location of family and social capital in existing neighborhoods (Horn, Ellen, and Schwartz, 2014; Bergman et al., 2024a), discrimination (Christensen and Timmins, 2022), and high search costs for recipients (Galiani, Murphy, and Pantano, 2015; Bergman et al., 2024a; Bergman, Chan, and Kapor, 2020; Aliprantis, Martin, and Phillips, 2022).

2018). This alternative subsidy cap was called Small-Area Fair Market Rent (SAFMR)[2] and would effectively raise the maximum subsidy in high-rent ZIP codes, and decrease it in low-rent ZIP codes, with voucher recipients continuing to contribute 30% of their gross income as rent. Following the initial success of SAFMR in reducing recipient poverty exposures in Dallas, HUD announced in late 2016 that public housing authorities in 24 metropolitan areas would be required to adopt SAFMR to determine a recipient's subsidy cap by April 2018.[3] Subsequently, in October 2023, HUD expanded this requirement to an additional 41 metropolitan areas, with implementation effective January 1, 2025. Despite this recent expansion, relatively little is known about the original 2018 implementation mandate[4]

In this paper, we use HUD-administrative data to investigate whether the poverty reduction outcomes observed in the initial SAFMR pilot in Dallas (Collinson and Ganong, 2018) were 'horizontally' scaled across alternative settings and populations, especially racial minorities, after the 2018 mandate (List, 2022). Similarly to Collinson and Ganong (2018), we focus on recipients who remained in the program before and after the mandatory implementation of SAFMR (2015-2019). We compare white and minority recipients to illuminate racial disparities and potential mobility barriers and evaluate variation across mandated metropolitan statistical areas to identify factors influencing policy effectiveness. Better understanding of the ability to horizontally scale earlier Dallas results to other settings is particularly relevant given the acknowledged challenges of scaling experiments from pilot settings to broader contexts (Pritchett and Sandefur, 2015; Banerjee et al., 2017; List, 2022; Al-Ubaydli, Lai, and List, 2023).

Challenges to identification include the non-random selection of metropolitan areas by HUD to impose the SAFMR mandate, and the presence of non-compliant public housing authorities (PHAs) who locally administer the program that either delayed or partially imple-

[2]For instance, under FMR, the monthly rental budget for a two-bedroom unit in Chicago was $1,265 in 2017, whereas under SAFMR the budget could range from $680 in the lowest SAFMR ZIP codes to $1,630 in the highest.

[3]The 24 mandatory metropolitan areas were determined based on 4 published criteria by HUD. The criteria for the mandate included the concentration of voucher recipients, relative low FMRs at the metropolitan level, availability of units in high-rent areas, and elevated vacancy rates.

[4]The one exception is Ellen, O'Regan, and Strochak (2024) who analyzed the the effect of the mandate on initial location decision of new recipients, who account for approximately 5% of recipients annually. How this study relates and complements those earlier results is discussed further below and in the conclusion.

mented the mandate. To address these issues, we employ a range of identification strategies informed by the detailed institutional context. Our preferred approach leverages the fact that PHAs in mandated metropolitan areas had discretion over the timing of SAFMR adoption for existing voucher recipients, but not new recipients. We assume that, at the household level, the timing of SAFMR adoption by their assigned PHA is essentially random, meaning that PHAs' decisions to actually implement SAFMR are independent of when individual new or renewal housing voucher contracts occur. As robustness checks, we examine several alternative specifications, including an event study design comparing mandated metropolitan areas - selected in April 2018 based on four observable criteria - with a set of 15 comparison metropolitan areas that closely resemble mandated ones by relaxing these criteria. We also implement an approach similar to that of Collinson and Ganong (2018) to further validate our findings.

Our findings reveal that the shift from metropolitan-wide FMRs to ZIP-code-level SAFMRs has distinct impacts on housing voucher recipients, influenced by both beneficiary characteristics and the broader metropolitan context. Among existing voucher holders, the annual move rate—historically around 14.5%—decreased slightly under SAFMR, indicating that this policy change did not substantially increase overall mobility. The reduced move rates can be partly attributed to voucher holders already residing in lower-poverty neighborhoods being less likely to move once SAFMRs were introduced. However, those who did choose to relocate under SAFMR ultimately settled in lower-poverty neighborhoods, suggesting that—while the policy may not increase the total volume of moves—it does promote higher-opportunity moves among those who decide to relocate. Taken together, these findings underscore the unique mobility barriers voucher recipients face when deciding whether to move, even when a policy reform is designed to incentivize relocation to lower-poverty areas.

Second, our findings indicate that White households benefit more from SAFMR, moving to significantly lower-poverty neighborhoods than African-American households. Specifically, White voucher holders were more than twice as likely to relocate to neighborhoods with poverty rates below 20%. This difference persists even though African-American households tend to move more frequently and travel farther, suggesting that higher search costs

and structural constraints remain mobility barriers for African-American households. These outcomes are not fully explained by household characteristics such as the presence of children or the age of the household head: although African-American voucher holders tend to be younger, have slightly higher incomes, and are more likely to have children than White voucher holders, they still experience smaller reductions in poverty exposure (Horn, Ellen, and Schwartz, 2014; Ellen, 2020). These findings point to the possibility that factors such as racial homophily (Aliprantis, Carroll, and Young, 2024; Bayer and McMillan, 2012), discrimination (Chan and Fan, 2023; Christensen, Sarmiento-Barbieri, and Timmins, 2021; Christensen and Timmins, 2022; Christensen and Timmins, 2023), and information or search frictions (McClure and Schwartz, 2019) may disproportionately affect African-American households under SAFMR. Moreover, our data show that White voucher holders were already living in lower-poverty neighborhoods before SAFMR—a pattern consistent with broader residential trends (McClure and Schwartz, 2019; Aliprantis, Martin, and Tauber, 2024). This baseline advantage, coupled with SAFMR's seemingly race-neutral design, can inadvertently perpetuate spatial inequalities. While SAFMR was introduced in Dallas partly to mitigate segregation, this study underscores the need for more targeted interventions to ensure equitable outcomes across racial groups (Aliprantis, Carroll, and Young, 2024; Aliprantis, Martin, and Tauber, 2024).

When comparing these findings to the Dallas demonstration (Collinson and Ganong, 2018)—which yielded larger standardized effects under SAFMR—the 2018 mandated rollout appears more muted overall. Much of this difference seems to stem from heterogeneity across metropolitan areas. Cities such as Fort Lauderdale (FL), North Port (FL), San Antonio (TX), Monmouth-Ocean (NJ), Washington, DC, and Gary (IN) show substantial poverty-reduction gains, whereas Bergen-Passaic (NJ), Charlotte (NC), Jacksonville (FL), and Sacramento (CA) experience more limited or even counterproductive outcomes (i.e., average neighborhood poverty rates increased). This heterogeneity appears to be driven by the efficiency with which African American households can relocate to areas of lower poverty. Specifically, a correlation analysis indicates that metros with a higher initial concentration of voucher holders in low-income neighborhoods achieve greater poverty reductions, underscor-

ing the importance of local context for policy success. Furthermore, in markets where African American voucher holders are more likely to be concentrated in areas of higher poverty, the effectiveness of the policy is limited. These patterns suggest that aligning SAFMR policies with local market conditions—and addressing the mobility barriers faced by minority households—may help enhance their effectiveness in promoting housing mobility and reducing poverty (Horn, Ellen, and Schwartz, 2014; Banerjee et al., 2017; List, 2022; Al-Ubaydli, Lai, and List, 2023; Bergman et al., 2024b).

The research contributes to at least three existing strands of literature. A substantial body of work examines how targeted interventions affect neighborhood choices for low-income families, consistently finding that neighborhood environments can shape long-term outcomes, including children's earnings and educational attainment (Chetty et al., 2014; Chetty, Hendren, and Katz, 2016; Chetty and Hendren, 2018; Chyn and Katz, 2021). This research also highlights persistent social and informational barriers, underscoring the importance of counseling and other search assistance in facilitating beneficial moves (Bergman et al., 2024a; Bergman et al., 2024b). Building on the Moving-to-Opportunity program literature (e.g., Jacob and Ludwig, 2012; Ludwig et al., 2013; Jacob, Ludwig, and Miller, 2013), recent studies emphasize that financial incentives—particularly through adjustments to voucher subsidy caps—can further improve outcomes by encouraging landlord participation and expanding housing options (Collinson and Ganong, 2018; Aliprantis, Martin, and Phillips, 2022). Indeed, raising payment standards in selected neighborhoods may help low-income households access areas with higher opportunity while simultaneously motivating landlords to offer more units to voucher holders (Phillips, 2017; Cunningham et al., 2018; Moore, 2018; McMillen and Singh, 2020). Our research adds to this body of work by leveraging extensive administrative data from multiple metropolitan areas, showing that the success of these policy changes depends not only on how financial subsidies are structured but also on the ability of voucher holders to navigate moving frictions.

Another strand of research investigates racial disparities in neighborhood choices, focusing on how minority households often face structural barriers to mobility. Large-scale administrative and tax data show that Black children experience persistently lower intergen-

erational mobility relative to White children, even when growing up in similar neighborhoods (Chetty et al., 2020). Although policies like SAFMRs aim to be color-blind, empirical evidence suggests that minority voucher holders continue to encounter reduced market access to lower poverty units (Horn, Ellen, and Schwartz, 2014; Christensen, Sarmiento-Barbieri, and Timmins, 2021; Christensen and Timmins, 2022; Chan and Fan, 2023). Our results corroborate these patterns: while White voucher holders tend to relocate less frequently overall, they secure greater gains in neighborhood quality when they do move. By contrast, African-American families remain more constrained to move to better socio-economic neighborhoods, limiting the policy's potential to bridge racial gaps. This persistent disadvantage points to the need for complementary policy measures—such as housing search assistance and more robust counseling programs—to ensure that financial incentives translate into equitable improvements in neighborhood outcomes.

Last, the research adds to a growing body of research on the importance of horizontal scaling—replicating smaller demonstrations across diverse contexts—to account for site selection bias, general equilibrium effects, and heterogeneous local incentives (Pritchett and Sandefur, 2015; Kline and Walters, 2016; Muralidharan and Niehaus, 2017; Allcott, 2015; Banerjee et al., 2017; Bold et al., 2018; Vivalt, 2020; Egger et al., 2022; List, 2022; Al-Ubaydli, Lai, and List, 2023). Our study extends this literature by systematically analyzing replicated interventions in the 2018-mandated metropolitan areas, providing evidence on how subsidy reforms operate under varying housing market conditions and administrative environments. In doing so, we highlight institutional challenges—such as the reluctance of PHAs to adopt SAFMRs without federal mandates or under predetermined housing market characteristics—that hamper broader metropolitan scaling. These findings underscore the necessity of addressing sub-local implementation barriers to achieve successful policy expansion and illustrate how context-dependent factors can shape the ultimate outcomes of place-based initiatives.

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 comparison with Dallas experiment. Section **??** discusses the cost-neutrality of the program. Finally, Section 6 concludes.

2 Institutional Background

2.1 Housing Voucher Program

Housing vouchers were first allocated nationwide through Section 8 of the US Housing and Community Development Act of 1974. The US Congress relabeled two earlier voucher variants as Housing Choice Vouchers (HCV) in 1998 and required recipients to contribute 30% of their household income in rent to private landlords, while the government covers the remaining gap up to a HUD determined Fair Market Rent (FMR). FMRs for are adjusted by bedroom size based on the family size of recipients and traditionally set equal to the 40th percentile of local asking rents in their metropolitan area.[5]

However, using a single metro-wide FMR as a subsidy standard forces households to trade off between structural and neighborhood quality. Figure 1 provides a conceptual illustration. As shown in Panel (a), when voucher holders are given a metropolitan-wide rent subsidy as a uniform budget, the resulting budget line slopes downward, thereby creating a trade-off between structure quality and neighborhood quality. In addition, because local PHAs set minimum housing standards, households cannot fall below a certain threshold of structural quality. As a result, constrained by a single metro-wide FMR, they may settle in lower-rent, higher-poverty areas to meet the structural quality requirement, leaving less "room" in the budget for neighborhood quality.[6]

Indeed, housing voucher recipients are much more likely to live in higher-poverty neighborhoods compared to other renters. Figure 2 illustrates this "excess concentration" (Erik-

[5]For example, the maximum monthly rental budget for a 2-bedroom unit in the Chicago Metro area (2017) was $1,232. For a household with an annual income of $14,000, their monthly contribution would be about $350 ($14,000 $\times$ 0.3 12). The subsidy for this family would then be $882 ($1,232 -$350).

[6]Panel (b) in Figure 1 illustrates an alternative scenario where the budget line is expanded (e.g., when the FMR is set at the 50th percentile of local rents rather than the 40th). In this case, although recipients can afford both better structural conditions and improved neighborhood quality, the trade-off between structural quality and neighborhood quality still exists.

sen, 2021) of HCV recipients in high-poverty neighborhoods (poverty rates above 20%).[7] The x-axis shows the percentage of all renters living in neighborhoods exceeding the 20% poverty threshold in the 50 largest U.S. metropolitan areas in 2017, based on the American Community Survey conducted by the U.S. Census Bureau. The y-axis represents the difference, in percentage points, between the share of HCV recipients in these high-poverty neighborhoods and the share of all renters in the same metropolitan area. On average, 39.7% of renters live in high-poverty neighborhoods, while 57.0% of HCV recipients do—an excess of 17.3 percentage points. Metropolitan areas with larger shares of renters in high-poverty neighborhoods tend to exhibit even more pronounced excess concentration of voucher holders.

These patterns raise questions about the HCV program's effectiveness in promoting genuine housing mobility. The persistent concentration of voucher holders in high-poverty areas suggests that more targeted policies may be needed to ensure equitable access to neighborhoods with better opportunities.

2.2 Small Area Fair Market Rents

HUD first defined SAFMRs in 2011 for Dallas. The SAFMRs adjusted the payment standards at the ZIP code level,[8] allowing for higher payments to landlords in neighborhoods with higher rents, while voucher holders still contributed 30% of their income towards rent.[9] The

[7] HUD and prior research often classify neighborhoods with poverty rates above 20% as high-poverty (e.g., Dastrup et al., 2018).

[8] For example, the maximum monthly rental budget for a 2-bedroom unit in the Chicago Metro area in 2017 could range from $680 to $1,630, depending on the ZIP code under the SAFMR. The SAFMR is calculated at the ZIP code level based on the current 5-year ACS Adjusted Standard Quality (ASQ) 40th percentile gross rent for a 2-bedroom unit, with data validation and adjustments. See FY2024 example for ZIP code 45219.

[9] Collinson and Ganong (2018) provided the first evidence of SAFMRs adoption in Dallas, Texas. They found that voucher recipients in Dallas, TX, experienced a shift to areas with lower rates of violent crime and poverty compared to voucher holders in nearby Fort Worth. The authors also noted that adjusting the rent ceiling through SAFMRs had a greater impact on neighborhood quality compared to uniformly raising the rent ceiling. Additionally, Dastrup, Finkel, and Ellen (2019) evaluated the effects of SAFMRs implementation in the five demonstration housing authorities with Dallas and Plano in Texas. They observed that voucher recipients in metropolitan areas with ZIP code level payment standards were more likely to reside in ZIP codes with higher rents, particularly those with children. Furthermore, as unit rents did not decrease proportionally to the reduction in subsidy, voucher holders who remained in low-rent neighborhoods faced increased rent contributions. Reina, Acolin, and Bostic (2019) show early evidence of SAFMRs demonstrations on helping voucher holders access to higher opportunity neighborhoods, and provide results that SAFMRs has mixed evidence on promoting access to opportunity neighborhoods other than Dallas (e.g.,

use of SAFMRs were expanded to 5 public housing authorities (Chattanooga, TN, Chicago, IL, Laredo, TX, Long Beach, CA, and Mamaroneck, NY) who volunteered to participate in demonstration projects in 2012 (Dastrup et al., 2018).

SAFMRs incentivize voucher holders to allocate more of their housing budget towards neighborhood quality rather than structure quality as compared to traditional FMR payment standards. Panels (a) and (b) in Figure 1 illustrate this conceptual shift. Under FMRs (Panel (a)), rent subsidies are uniform across a metropolitan area, while SAFMRs (Panel (b)) adjust subsidies based on neighborhood quality. This variation encourages recipients to prioritize better locations while maintaining a consistent level of structure quality. The resulting horizontal budget line reflects this dynamic, as ZIP code-based subsidy standards allow households to upgrade neighborhood quality without compromising structure quality.

In late 2016, HUD announced two significant changes to voucher rent ceilings. First, all public housing authorities in a metropolitan area were allowed to adopt SAFMRs for determining rent ceilings for HCV recipients starting in the 2017 fiscal year. Second, public housing authorities in 24 mandated Metropolitan Statistical Areas (metropolitan areas) were required to adopt SAFMRs for determining rent ceilings for all HCV recipients starting in 2018. These mandated metropolitan areas were selected based on specific criteria.[10] An important difference between the 2018 SAFMR-mandate analyzed in this research and the earlier demonstrations started in 2012 is that the 5 PHAs participating in those demonstrations volunteered.

- Number of Voucher Holders: At least 2,500 vouchers were in use in the metro area
- Low metropolitan FMRs: At least 20 percent of the standard quality rental stock, within the metropolitan FMR area is in small areas (ZIP codes) where the Small Area FMR is more than 110 percent of the metropolitan FMR;

living in lower opportunity neighborhoods after SAFMRs implementation for some demonstration sites). Park (2024) shows the impact of SAFMR on rental market and spatial distribution of voucher holders across neighborhoods, and finds it causes rents increased in high-rent neighborhoods but declined in low-rent areas.

[10] 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 on SAFMRs, November 16, 2016 for details.

- Vouchers concentrated in low-opportunity neighborhoods: 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.

- High vacancy: The vacancy rate for the metropolitan area is higher than 4 percent.

HUD mandated the use of SAFMRs by Public Housing Authorities (PHAs) in the 24 metropolitan areas starting no later than April 1st, 2018. However, voucher recipients whose voucher issued by these PHAs may not start using the new SAFMR based payment standard immediately. For example, a voucher holder with contract renewal date as 1st May every year, her subsidy amount will be re-examined and updated based on her location (ZIP Code) at the renew date, which is one month later after the mandated date. On the flip side, any newly issued voucher will immediately use the SAFMR based payment standard if their contract start date is after the mandated date of April 1st, 2018. Table 1 provides information on the 15 metropolitan areas in our sample[11] out of the 24 mandated metropolitan areas that meet the specified criteria and were designated as mandated metropolitan areas by HUD.

Relatively few papers have examined the implemenation of mandatory SAFMRs starting in 2018. Ellen, O'Regan, and Strochak (2024) find that new voucher holders—those entering the program for the first time—successfully moved to higher-rent areas without adversely affecting the lease-up rates of these new recipients. Meanwhile, Aliprantis, Martin, and Phillips (2022) focus on landlords' responses to the 2018 SAFMRs in Washington, D.C., finding minimal changes in landlords' background-check processes and only a small-scale response to the new policy overall.

[11]Detailed descriptions of why we use these 15 metropolitan areas are provided in Appendix A.

3 Empirical Setting

3.1 Data

HUD Administrative Data The administrative data on voucher recipient attributes and locations used in this study were obtained from the U.S. Department of Housing and Urban Development (HUD) under a restricted data use agreement. The dataset tracks household information each time a participant is admitted, undergoes an annual examination for contract renewal, or exits the program. It includes annual information on family composition, demographics, and addresses for individuals who used a housing voucher between January 2015 and December 2019. Additionally, the dataset provides details on voucher contracts, such as admission and allocation dates, contract start or renewal dates, administering Public Housing Agencies (PHAs), and data on subsidy amounts and rents.

Building on these data, we developed a novel method to determine—on a year-by-year basis—whether a voucher holder's payment standard was based on the FMR or the SAFMR at the time of lease start or renewal. Specifically, at each observation, we verify whether the effective payment standard corresponds to the FMR or SAFMR for the household's current ZIP code and check if the household has moved since the last observation. This approach uniquely allows us to identify individuals who genuinely received SAFMR-based subsidies, making it, to the best of our knowledge, the first such attempt in the literature. Further details and fact-checks are provided in Appendix A.

Following HUD's selection criteria, our location characteristics (i.e., census tract poverty rate) are from the American Community Survey that were directly acquired from the original administrative data. These location characteristics are recorded at the beginning of our sample period and remain consistent throughout the sample period to avoid any errors. Furthermore, using the subsidy information, we developed our own method to identify individuals if they received the SAFMR-based payment standard.[12] To the best of our knowledge, this is the first attempt in the literature to do so. Details are discussed in the

[12]We compare the household level Effective Fair Market Rent (EFMR), that if it is equal to SAFMR, we define this households are using SAFMR-based payment standard. Otherwise, they are still using the metro-wide Fair Market Rent as their payment standard benchmark

Appendix A.

Sample Construction By leveraging a household-level unique identifier, we can construct our data set in a panel format. This longitudinal structure enables us to distinguish between new voucher holders, individuals entering the program for the first time, and existing voucher holders who have participated in the program for more than a year. These two groups differ in both their mobility decisions and in how SAFMRs are applied to their payment standards.[13] In this paper, we focus on existing voucher holders which comprise more than 95% annual samples.

Table 2 presents summary statistics for the voucher recipients sample in 2017. Of the 171,918 recipients included, 3.44% were first-time voucher holders who entered the program that year, while the remaining 96.56% had been in the program for more than a year. The average tract poverty rate among these recipients was 23.12%, and 46.1% lived in tracts with a poverty rate below 20%. The majority of household head were African American (67.2%), most were female-headed (84.7%), and over 30% are above age of 50 and 50% are between 40 to 60 years old. Further details on sample construction can be found in Appendix A.

Selection of Comparison Metropolitan Areas As discussed in Section 2, HUD designated 24 metropolitan areas for the SAFMRs mandate based on four published criteria. We focus on 15 mandated metros that either did not already have voucher mobility interventions in place or presented no issues with the data we obtained (see Appendix A for details).

When evaluating the 2011 Dallas SAFMR experiment—which serves as a key reference

[13]Specifically, first-time voucher holders often seek a new unit to utilize on the increased rental budget offered by the voucher program. For first-time voucher holders, (representing approximately 5% of all voucher holders annually) admission typically involves being placed on a waiting list by their PHAs. The waiting time for an HCV averages 28 months in 1998 after first applying (See Waiting In Vain: An Update on America's Rental Housing Crisis, HUD 1999), but in some extreme cases can extend to 72 months (6 years). Once applicants pass the screening process and are issued a voucher, they must secure a suitable housing unit within at least 60 days (it can be 90 or 120 days, based on administrating PHAs or pre-existing condition of voucher holders. See HUD No. 24-222). Upon entering the program, the SAFMRs are immediately applied as the payment standard, if their respective PHAs have adopted SAFMRs as payment standards. In general, to take advantage of the generous rental subsidies, these new voucher recipients must find both a new unit and a landlord willing to accept their vouchers. We do not observe their prior locations or waiting times, as we lack voucher applications data. For more details about the first time voucher holders, refer to Ellen, O'Regan, and Strochak (2024).

point—Collinson and Ganong (2018) use voucher holders in Fort Worth as the control group. Fort Worth closely resembles Dallas in many respects, including their geographic proximity and dual-city structure within a large metropolitan area; however, SAFMRs were not implemented there. By comparing the outcomes of the two areas, the authors identify the effect of SAFMRs on the locational choices of voucher holders.

In an ideal scenario, we would identify similar comparison metropolitan areas for each of the 2018 mandated metropolitan areas in our sample—metropolitan areas that closely resemble the 2018 mandated areas but where SAFMRs was not implemented. However, finding suitable control groups for all mandated metropolitan areas is challenging, especially given the need for geographic proximity, not to mention the neighborhood similarity. To address this limitation, we leverage the HUD selection rule for the 2018 mandated metropolitan areas. Our comparison group consists of existing voucher recipients from 15 non-mandatory metropolitan areas that met the four HUD criteria but were ultimately not selected or met only three of the four. We provide detailed descriptions of these areas and their selection procedures in Appendix A, along with summary statistics in Table A1. These "near-mandatory" areas closely resemble the mandated metros in terms of observable characteristics. As shown in Appendix B (alternative control group) and in our robustness-check event-study analyzes, these areas did not display significantly different pre-trends in our primary neighborhood-poverty outcomes. Furthermore, additional robustness checks confirm that various choices of comparison groups do not affect the empirical results.

3.2 Descriptive Insights

In this subsection, we present descriptive and novel insights about housing voucher recipients and the SAFMRs-mandate that guide the subsequent empirical analysis.

3.2.1 PHAs Do Not Voluntarily Adopt SAFMRs Without a Mandate

As described in Section 2, since 2017 all Public Housing Agencies (PHAs) have had the option to voluntarily adopt SAFMR for determining rent ceilings in the Housing Choice Voucher (HCV) program. Figure 3 compares PHA-level adoption rates in 2018 for mandatory

metropolitan areas (Panel (b)) versus the 50 most populous non-mandatory metropolitan areas (Panel (a)). The y-axis represents the SAFMR adoption rate, and the x-axis shows the contract start or renewal month-year. Circle sizes reflect the relative number of vouchers allocated by each PHA.

Panel (a) of Figure 3 indicates that by the end of 2019, virtually none of the PHAs in the 50 largest metropolitan areas had voluntarily adopted SAFMR payment standards, despite having the option. Similarly, Panel (b) shows that prior to the mandate's start in April 2018, almost no PHAs in mandatory metropolitan areas used SAFMRs. Once the mandate took effect, most PHAs reached over 90% compliance, although the timing of adoption varied. This variation provides an opportunity to identify the policy's effects, as discussed in later sections.

The reasons for the lack of voluntary adoption before the mandate and the partial non-compliance afterward are not entirely clear. One potential explanation is limited management capacity, including insufficient computer systems needed to link each unit address with its appropriate locational payment standard. Unlike earlier demonstrations in 2011 and 2012, to the best of our knowledge, the mandated PHAs in 2018 did not receive the $50,000 technical support grants to facilitate implementing the new standards or communicating the changes to staff and recipients.[14]

3.2.2 Subsidies Under SAFMR

Figure 4 illustrates the relationship between the ZIP code–level rental prices (represented as the ratio of the SAFMR to the FMR) (horizontal axis) and the median value (in each bin) of housing subsidies (vertical axis) for 2017 (blue squares) and 2019 (red circles). The sample focuses on voucher recipients in the 15 metropolitan areas required to adopt SAFMRs and appeared both in year 2017 and 2019 to rule out any impact of entering and exiting.

[14]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 SAFMR payments. Although the administrative fee is linked to local federal government wage indexes and additional factors—such as program size, benefit load, the percentage of households with earned income, the rate of new admissions, and the distance from the PHA's headquarters—factors related to SAFMRs were dropped due to public comments. See HUD Publishes Revised New Administrative Fee Formula.

Each dot represents the average subsidy for one of the 20 quantiles of the SAFMR/FMR distribution.

A clear pattern emerges when comparing 2017 to 2019: lower-rent ZIP codes (i.e., SAFMR < 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 lower-rent areas. 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.[15] As a result, the effective financial incentive to move to higher-rent neighborhoods remains modest for incumbent voucher holders, since the potential subsidy increases often do not fully offset moving costs.

3.2.3 Racial Differences in Neighborhood Selection

Racial differences in neighborhood choices among housing voucher holders offer valuable insights because all racial groups must meet the same income eligibility criteria and receive subsidies on the same terms, yet still exhibit distinct locational patterns. As shown in Panel A of Table 2, approximately 67% of voucher recipients in our data are African American, 30% are White, and 3% identify with other racial groups. Although voucher programs are theoretically color-blind—basing eligibility and rental budgets solely on income—the statistics in Panel B of Table 2 reveal notable racial disparities in neighborhood selection.

First, African-American voucher holders are more likely to reside in higher-poverty areas, with an average neighborhood poverty rate of 24.45% in 2017, compared to 20.40% for White households. Figure 5 corroborates this finding: it plots kernel densities of the poverty rates in neighborhoods where African-American and White voucher recipients lived in 2017 (pre-SAFMR) versus 2019 (post-SAFMR). In 2017, a larger proportion of White recipients lived in areas with poverty rates below 20%. After SAFMR was implemented in 2019, the overall distribution for each group remained largely unchanged (Panel (c)), suggesting that racial

[15] 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 SAFMR to 130 percent in the first year, to 120 percent in the second, and eventually align it with the PHA's standard. See HUD Final Rule on SAFMRs, November 16, 2016.

disparities in exposure to neighborhood poverty persisted. Indeed, SAFMR may not have alleviated preexisting racial inequalities in neighborhood choice and may have even reinforced them.

This disparity in poverty exposure is especially striking given that, as shown in Panel B of Table 2, African-American voucher holders have higher monthly incomes than their White counterparts. Additionally, African-American households move more often, with an annual moving rate of 16.07%—nearly 50% higher than the 11.63% rate for White households. When African-American households do relocate, they move significantly farther on average (13.87 miles versus 11.32 miles for White households),[16] implying greater search costs and more challenges in finding a suitable unit.[17]

Finally, African-American voucher holders were also more likely to have younger, female heads of household and children. In the main empirical sections, we will examine whether these demographic characteristics—and the introduction of SAFMRs—help explain the observed racial differences in location choices and neighborhood outcomes.[18]

3.2.4 Regional Variations among Mandatory Metropolitan Areas

Table 1 provides a snapshot of the 15 metropolitan areas selected by HUD for mandatory SAFMR adoption in April 2018. These metropolitan areas differ considerably in (i) the absolute size of the voucher program (ranging from over 32,000 voucher holders in Philadelphia–Camden–Wilmington to fewer than 2,592 in North Port–Bradenton–Sarasota), (ii) the concentration of voucher holders in high-poverty or low-income neighborhoods, and (iii) broader housing-market indicators such as the rental vacancy rate. HUD chose these metropolitan areas precisely because they had some of the highest rates of voucher concentration coupled with enough vacant housing in low-poverty areas that a shift in payment

[16] Median moving distance for moved households are 2.91 miles (African-American headed) and 2.01 miles (White headed), respectively.

[17] These findings align with Ellen, O'Regan, and Strochak (2024), which reports that Black and Hispanic voucher recipients are less likely to lease up than White recipients, primarily due to higher search costs and more limited unit availability. The study uses data from about 85,000 new voucher recipients annually across 433 metropolitan housing authorities (2015–2019).

[18] For example, female headed households still have racial difference in poverty reduction and the pattern is almost identical compared with the full sample.

standards might encourage movement into less disadvantaged neighborhoods.

Beyond these indicators, the demographic composition of voucher holders across neighborhoods also varies sharply across metropolitan areas, as we document in Appendix Table D4. In general African-American headed voucher holders are more likley to reside in high-poverty (e.g., above 20% poverty rate in census tract) areas compared with White voucher holders. For example, some areas such as Bergen-Passaic (NJ), Philadelphia (PA) have a particularly higher share of African-American voucher holders residing in high-poverty areas, compared to White voucher holders.

As demonstrated in earlier SAFMR studies (Dastrup et al., 2018; Reina, Acolin, and Bostic, 2019), these sorts of site-specific features—ranging from the size of the voucher population to its racial composition—can generate heterogeneous outcomes that may not uniformly improve opportunity for all voucher recipients. We therefore expect the 2018 mandated sites, which are more numerous and diverse, to exhibit significant regional variation as well—a finding we elaborate on further in later sections[19].

3.3 Identification Strategy

Two main concerns threaten a causal interpretation of the impact of the 2018 mandate on voucher holder locations: (1) HUD may have selected metropolitan areas for the mandate based on unobserved factors or pre-existing trends, and (2) PHAs may have selectively applied SAFMRs to certain households. For instance, HUD might have targeted areas experiencing rising neighborhood poverty concentrations, or PHAs could have offered SAFMRs preferentially to families already inclined (or disinclined) to seek lower-poverty neighborhoods. To address these concerns, we carefully construct treatment and comparison groups,

[19]It is worth noting that contextual differences extend beyond the housing market itself. Each MSA hosts one or more Public Housing Agencies (PHAs), which vary in administrative capacity and often serve geographically segmented or partially overlapping sub-regions. Thus, even within a single MSA, the location patterns of voucher holders may differ across PHAs, heightening the context dependency of the SAFMR rollout. As emphasized in the broader policy literature (Banerjee et al., 2017; Pritchett and Sandefur, 2015; Al-Ubaydli, Lai, and List, 2023; List, 2022), scaling up any policy from a small demonstration to a broader mandate can expose such local-level complexities. In the case of SAFMRs, both the initial housing market conditions and the PHA administrative structure shape how voucher households respond, including the distribution of African American and White voucher holders among high- and low-poverty neighborhoods.

exploit institutional details to directly observe payment standards, and closely examine the timing and assignment mechanisms affecting voucher recipients.

Regression Specification Our core sample consists of households from both the 15 metropolitan areas and the 15 near-mandatory metropolitan areas described in Section 3.1. Voucher holders who acquired their vouchers before the mandatory date, will renew their contracts and update their payment standard into SAFMR-based, on the "anniversary" of the initial/previous year contract signing. This fact is directly observed from our data and provides exogenous variation (timing of contract renew is decided by previous or initial leasing date) for our identification.

We estimate the following regression for household i in PHA p, located in county c (nested within metropolitan area m), observed in year-month $t \in \{\text{Jan } 2015, \ldots, \text{Dec } 2019\}$:

$$Y_{i,p,m,t} = \alpha + \beta \, \mathbb{I}(\text{PayStand=SAFMR})_{i,p,m,t} + \eta_i + \delta_c + \zeta_t + \epsilon_{i,p,m,t}, \tag{1}$$

where $\mathbb{I}(\text{PayStand=SAFMR})_{i,p,m,t}$ is an indicator for whether household i's renewed voucher subsidy in year-month t is based on SAFMRs (see Appendix A for details). The model includes household fixed effects η_i, county fixed effects δ_c, and year-month fixed effects ζ_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 Fair Market Rents (FMR) or the new SAFMRs, while controlling for any time-invariant household attributes.

Our primary outcome variable is $Y_{i,p,m,t}$, the neighborhood poverty rate (drawn from 2010 Census data) of household i's Census tract. We measure poverty using 2010 data to lessen concerns that voucher holders themselves might drive neighborhood-level demographic changes. Standard errors are clustered at the county-PHA-year-month level to account for correlated shocks within these units.

Identification Assumption and Robustness The key identifying assumption is that a PHA's shift to SAFMR for an existing household's annual contract renewal is effectively exogenous from the household's perspective. The anniversary date of each voucher's initial

contract is determined well in advance, limiting the household's ability to adjust the renewal schedule in response to knowledge of (or preferences regarding) SAFMR. Moreover, in mandated metropolitan areas, PHAs typically implement SAFMR at the earliest allowable time to comply with HUD rules, and they do not systematically notify voucher holders of their exact adoption date (Figure 3). As a result, strategic timing by recipients—where households could "wait out" or "jump in early" to exploit the new policy—is highly unlikely.

To further validate our main results, we perform multiple robustness checks that leverage alternative identification strategies and address potential confounding factors. First, we employ an event-study framework to compare the neighborhood outcomes of voucher recipients in mandated metropolitan areas with those of otherwise similar recipients in non-mandated areas. Second, we use an instrumental variable (IV) approach, where the local PHA's peer-based compliance rate serves as an instrument for actual SAFMR uptake. Third, we contrast our baseline specification with a standard difference-in-differences framework (Collinson and Ganong, 2018), confirming that the estimated effects remain consistent. Finally, we also present results using alternative definitions of control groups. Collectively, these checks reinforce our conclusion that the observed reductions in neighborhood poverty rates are driven by the SAFMR policy, rather than by unobserved mobility intentions or preferences.

4 Full Sample

4.1 Overall Results

Effect on Poverty Table 3 presents the impact of SAFMR payment standards on the tract-level poverty exposure of existing voucher recipients. Overall, SAFMR adoption reduced the average tract poverty rate by 0.1834 percentage points. Given 14.54% of existing voucher holders moved in 2017, this estimate can be interpreted as the intent-to-treat (ITT) effect—i.e., the average impact on all existing voucher recipients, whether or not they moved.[20]

[20]The move rate is calculated as the number of voucher households with any change of address (i.e., current address differing from the last observed address) divided by the total number of voucher households in the calendar year, consistent with Collinson and Ganong (2018).

Following Collinson and Ganong (2018), we divide the policy effect by the move rate to estimate the treatment-on-treated (TOT) effect—i.e., the effect specifically for those who moved:

$$\frac{-0.1834}{0.1454} \approx -1.26 \text{ percentage points},$$

which represents about 5.5% of the 23.12% average poverty rate exposure in 2017.

SAFMR also increased the likelihood of locating in a tract with less than 20% poverty by 0.0091 percentage points. For movers, the TOT effect is:

$$\frac{0.0091}{0.1454} \approx 0.0626 \text{ percentage points},$$

or about 13.6% of the 0.4609 baseline. Similarly, the probability of locating in a tract with less than 10% poverty increased by 0.0061 percentage points overall. For movers, the TOT effect is:

$$\frac{0.0061}{0.1454} \approx 0.0420 \text{ percentage points},$$

or about 21.6% of the 0.1943 baseline. These results highlight that the benefits of SAFMR for existing voucher recipients primarily occur through residential mobility: although only a fraction of recipients move, those who do experience substantially greater reductions in poverty exposure. Compared with the previous demonstration (displayed in the Appendix Table 8), the magnitude is very similar (-0.2277 to -1.4187), except for Plano (TX), which shows increases in poverty after the introduction of SAFMR. For example, the standardized poverty reduction in Mamaroneck is '-1.4187', with a lower move rate of 7.00%. Our results are consistent with the previous literature that documented the heterogeneity in policy effectiveness as shown in Reina, Acolin, and Bostic (2019).

Effect on Mobility Table 4 reports estimates of the impact of SAFMR payment standards on the mobility of existing voucher recipients, measured by any change in address during

the previous calendar year.[21] Column (1) shows that, on average, SAFMR adoption led to a surprising decrease in overall mobility rates among existing voucher holders. This outcome is primarily driven by the 46% of recipients who were already living in tracts with poverty rates below 20% in 2017—i.e., low-poverty areas (Column (2)). For this group, SAFMR adoption significantly reduced mobility, by an average of 0.74 percentage points (5.6%). This decline is unsurprising, as recipients in low-poverty areas (often with higher rents) have weaker financial incentives to relocate.

By contrast, Column (3) focuses on recipients residing in tracts with poverty rates above 20% in 2017. For this group, SAFMR adoption is associated with a small decrease in mobility, though the effect is not statistically significant.

Overall, these findings highlight the nuanced nature of evaluating policy effectiveness for existing voucher holders. While the SAFMR policy offers financial incentives to move to lower-poverty areas, relocation costs dampen mobility—especially for recipients already living in low-poverty neighborhoods. However, among those who do move, SAFMR produces substantial reductions in poverty exposure. Thus, the policy's overall effectiveness in lowering poverty exposure hinges significantly on recipient mobility and the baseline conditions of the neighborhoods in which they live. Compared with Dallas (16.66% in 2010), the move rate in mandatory metropolitan areas is relatively lower, that the move rate in mandatory metropolitan areas is more consistent with previous demonstrations in Plano (TX, 13.74%), Chattanooga (TN, 12.44%), Chicago (IL, 15.05%), and much higher compared to Long Beach (CA, 9.93%) and Mamaroneck (NY, 7%).

4.2 Effect by Race

We next document the emergence of racial disparities in the policy's impact. As shown in Section 3.2, White households were more likely than African-American households to reside in lower-poverty neighborhoods before the adoption of SAFMR, raising concerns about the equitable distribution of voucher programs. This pattern is especially noteworthy because all racial groups must meet the same income eligibility criteria and receive uniform subsidies,

[21] Standard errors are clustered at the MSA-PHA-month level; household fixed effects are not included.

yet they exhibit distinct patterns in neighborhood choice—underscoring the high mobility barriers potentially faced by African-American voucher holders. The reason behind it may be associated with discrimination, search costs, and initial locations and neighborhood conditions.

Effect on Poverty Table 5 presents an analysis of existing voucher holders by the race of the household head (White or African-American).[22] The findings show that although both groups reduced their poverty exposure under SAFMR, White households (Column (2)) achieved reductions more than twice as large as those of African-American households (Column (1)). These estimates include household fixed effects, thereby accounting for time-invariant household-level characteristics.

Moreover, White households were more likely to relocate to neighborhoods with poverty rates below 20% with SAFMR, highlighting persistent racial disparities. Prior to SAMFR mandatory implementation (2017), 57% of White households already lived in lower-poverty neighborhoods, compared to only 41% of African-American households, suggesting that SAFMR may inadvertently perpetuate these disparities.

Such disparities in policy effectiveness highlight the barriers that continue to hinder the access of African-American voucher recipients to lower-poverty neighborhoods, despite the ostensibly race-neutral framework of SAFMR.

Effect on Mobility We also examine whether the introduction of SAFMR affects moving behavior differently across racial groups by analyzing changes in the probability of moving among African-American and white households. As discussed in Section 3.2, African American households tend to move more frequently and over longer distances than White households, reflecting higher search costs and reduced unit availability.

Table 6 shows that the overall moving frequency of African-American households decreases under SAFMR, while White households also move less frequently after the implementation of SAFMR, but experience a larger decrease. One possible explanation is that

[22] Appendix Table X indicates minimal differences between non-Hispanic White and Hispanic White households.

White households already tend to reside in lower-poverty neighborhoods, which reduces their incentive to relocate under SAFMR.

These patterns imply that the introduction of SAFMR may dampen mobility for households already in relatively low-poverty tracts, while also moderately reducing mobility among African-American households, who may still face significant barriers to relocating to lower-poverty areas. Consequently, the effectiveness of SAFMR in promoting moves to low-poverty neighborhoods appears to vary across racial groups, partly due to differences in baseline neighborhood conditions and search constraints.

School-aged Kids × Race As shown in Panel B of Table 2, African-American 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). To investigate whether the interaction of race and having children drives differences in policy effectiveness, we stratify households by whether they have school-aged children (defined as ages 6–12) at the time they were first observed.

In Table 7, columns (1) and (2) compare all households without and with school-aged children, respectively. Columns (3) and (4) focus on African-American households without and with children, while columns (5) and (6) do the same for White households. Overall, the presence of children does not substantially alter the policy's effectiveness in reducing poverty exposure. Among African-American households, those with school-aged children do experience slightly smaller reductions in poverty exposure, but these differences are not statistically significant. The same pattern emerges for White households.

However, the most pronounced gap in policy effectiveness appears between African-American households with school-aged children (column (4)) and White households with school-aged children (column (6)). This finding is particularly concerning because moving to lower-poverty neighborhoods can significantly benefit children's long-term outcomes (Chetty, Hendren, and Katz, 2016).

Overall, the introduction of SAFMR appears to reinforce existing patterns of racial segregation by producing larger reductions in poverty exposure for White households. These results underscore the importance of understanding the distinct mobility barriers faced by

African-American voucher holders in each market, including racial preferences, higher search costs, more limited unit availability, and broader structural challenges. Although investigating the root causes of racial segregation lies beyond the scope of this paper, our findings indicate that the benefits of SAFMR may not be shared equally across racial groups.

4.3 Robustness Checks

In this section, we present several robustness checks and explore alternative specifications to address potential concerns about our main regressions.

Event Study Approach As our first robustness check, we compare the poverty exposure of voucher recipients in mandated metropolitan areas with that of otherwise similar recipients in nonmandated areas (identified in Section 3.3), using an event-study framework. Specifically, for household i in metro m, county c, and month-year t, we estimate the following.

$$\mathrm{Y}_{i,m,t} = \sum_{t} \beta_t \times \mathrm{Mandatory}_m \times \mathrm{Post}_t \; + \; \eta_i \; + \; \delta_c \; + \; \zeta_t \; + \; \epsilon_{i,m,t},$$

where $\mathrm{Mandatory}_m = 1$ for April 2018 mandated metropolitan areas. We include household, county, and month-year fixed effects, and cluster standard errors at the county-PHA-contract start time (year-month) level. The event-study coefficients are aggregated into quarterly increments, with the fourth quarter of 2017—just before the SAFMR mandate—as the baseline. Outcome variables include the Census tract poverty rate (Panel (a)), an indicator for living in a neighborhood with a poverty rate below 20% (Panel (b)), and an indicator for neighborhoods with a poverty rate below 10% (Panel (c)).

As shown in Figure 6, there are no pronounced pre-trends between mandatory and comparison metros before April 2018, supporting a parallel-trends assumption. Starting in the first quarter of 2018, however, we observe an immediate reduction in average tract poverty rates, as well as an increase in the likelihood of living in neighborhoods with poverty rates below 20% and 10%. These effects become statistically significant shortly after the mandate takes effect.

The event-study estimates of the "treatment-on-treated" effect show a similar reduction in neighborhood poverty combining the year of 2018 and 2019 (-1.2462) compared with the estimates reported in Table 3 (-1.2613), yet remain closely aligned in direction and magnitude.[23] This difference reflects the nature of the event study and also the effectiveness of the policy that the voucher holders needs time to know and utilize the new payment standard. It also captures an average effect across the entire metropolitan areas (including voucher holders who have not yet renewed under SAFMR), rather than pinpointing the precise month a household transitions to the new payment standard. Consequently, they reinforce and support the main finding that SAFMR implementation decreases the neighborhood poverty exposure of voucher recipients.

Instrumental Variable Approach Next, we address potential identification issues by introducing an instrumental variable approach. In our main specification, the SAFMR payment standards for individual voucher holders (i.e., $\mathbb{I}(\text{PayStand=SAFMR})_{i,p,m,t}$ in Equation (1)) may be endogenous if, for example, PHAs target the enhanced subsidy to households with an explicit desire to move to lower-poverty areas, or to those who would otherwise not move without an extra incentive. Although the estimates in Table 3 include household fixed effects and demographic controls that may capture most of the factors that affect the households' moving decisions, the OLS results could still be biased if time-varying unobserved household characteristics are correlated with both the use of the SAFMR payment standard and the location choices of households.

To address this concern, Appendix Table B1 presents two-stage least squares (2SLS) estimates in which we instrument the use of SAFMR payment standards with the PHA's peer-based compliance rate. This compliance rate—i.e., the proportion of recipients within a PHA who receive SAFMR payment standards—largely depends on the HUD mandate that began in April 2018 and on the capacity (or management practices) of individual PHAs, making it unlikely that a single household's situation would influence the PHA's overall compliance decisions. Appendix B provides additional details on this instrumental variable

[23] Estimates are between - 0.9670 to -1.1870 in the year of 2018 and much higher in 2019 (the highest reduction is -2.1651 in the second quarter of 2019).

strategy, including validity of the first stage. Overall, the 2SLS results are statistically indistinguishable from the OLS estimates.

Alternative Control Group Finally, we explore results using alternative control groups. Table B2 presents findings obtained by selecting comparison metropolitan areas following Ellen, O'Regan, and Strochak (2024), who use a similar approach to evaluate lease-up rates for first-time voucher holders. Their method parallels ours in choosing comparison metropolitan areas, but instead of relaxing four benchmarks, they relax only two (voucher concentration in low-income areas and the requirement that all units under SAFMR must be at least 110% of MFMR), while ensuring the other two criteria remain met. Consequently, the comparison metropolitan areas overlap a lot with those in our sample,[24] while also adding new metropolitan areas for which complete data are available.[25] Overall, these results closely resemble those of our main specifications.

5 Horizontal Scaling of SAFMR

The mandatory expansion of SAFMRs in 2018 can be viewed as a scaled-out version of the earlier small-scale demonstrations in the Dallas metro area (2011) and five public housing authorities (2012). An established literature has examined the challenges of scaling policies from small experiments to larger contexts (Banerjee et al., 2017). One of the major challenges in horizontally scaling SAFMRs is context dependence—that is, treatment effects often depend on observed or unobserved characteristics of the locations where the intervention is implemented. Failing to account for these variations can lead to misleading conclusions about policy effectiveness when applied broadly.

[24] Cincinnati-Middleton, OH-KY-IN HUD Metro FMR Area, St. Louis, MO-IL HUD Metro FMR Area, New Orleans-Metairie-Kenner, LA HUD Metro FMR Area, Oklahoma City, OK HUD Metro FMR Area, Omaha-Council Bluffs, NE-IA HUD Metro FMR Area, Oakland-Hayward-Berkeley, CA Metro Division, Birmingham-Hoover, AL HUD Metro FMR Area, Middlesex-Somerset-Hunterdon, NJ HUD Metro FMR Area

[25] Boston-Cambridge-Quincy, MA-NH HUD Metro FMR Area, Baltimore-Columbia-Towson, MD MSA, Charleston-North Charleston-Summerville, SC MSA, Miami-Miami Beach-Kendall, FL Metro Division, Columbus, GA-AL MSA, Fort Wayne, IN MSA, Detroit-Warren-Livonia, MI HUD Metro FMR Area, Memphis, TN-MS-AR HUD Metro FMR Area, Houston-Baytown-Sugar Land, TX HUD Metro FMR Area, Boise City-Nampa, ID HUD Metro FMR Area, Austin-Round Rock-San Marcos, TX MSA

Given the significant policy and budgetary implications of SAFMRs, understanding how and why treatment effects vary between contexts is critical to ensuring their broader success. Based on this, we first compare the effectiveness of SAFMR in our 2018 mandatory metropolitan areas with the estimates of the Dallas expansion (2011) reported by Collinson and Ganong (2018). This comparison allows us to assess the consistency of policy outcomes when scaling interventions. We then investigate further heterogeneity at the MSA level in the 2018 mandated metropolitan areas, examining factors that may explain variations in effectiveness.

5.1 Comparison with the 2011 Dallas Demonstration

We first benchmark our standardized estimates for existing voucher holders under the 2018 mandate against the 2011 Dallas experiment analyzed by Collinson and Ganong (2018). Table 8 (Panel A) presents their results (Table 4 in Collinson and Ganong (2018)), comparing pre- (2010) and post- (2013) SAFMR outcomes in Dallas (treatment) and Fort Worth (control). The authors employ a difference-in-differences design—clustering standard errors at the Census tract level—to identify the impact of SAFMR. Their overall intent-to-treat (ITT) estimate (Column (7)) includes both movers and non-movers, while 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 all Census tracts' poverty rates in Dallas (Column (9)) as reported in Collinson and Ganong (2018), is -0.188.

To facilitate a direct comparison, we replicate this methodology using our sample of mandated metros (treatment) and their respective comparison metros, focusing on the period before (2017) and after (2019) SAFMR. Panel B of Table 8 presents these results, where Column (7) reports the ITT estimates (with tract-level clustered standard errors), 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 treatment-area Census tracts). While the results show a poverty-reducing effect, the magnitude of the standardized effect (-0.0767) is noticeably smaller than in the 2011 Dallas case.

Next, we apply our identification strategy from Section 3.3 to the Dallas sample of 2009-2013. Figure 7 (with point estimates presented in Panel A and Panel B of Table D2) reports these estimates.[26] Compared to the results in Table 8, our empirical approach yields slightly larger estimates than the method used by Collinson and Ganong (2018) for both the 2011 Dallas expansion (Panel A: -0.2304, column (5)) and the 2018 mandated metropolitan areas (Panel B: -0.1020, column (5)). This difference arises because our approach specifically identifies households that actually transition to SAFMR payment standards, whereas the method in Table 8 averages over all voucher holders in the treatment and comparison area. Despite these differences, consistent with Table 8, we find a larger standardized effect in Dallas than in the 2018 mandated metro sample. In the following section, we demonstrate that the muted results for the 2018 phase primarily stem from substantial heterogeneity between metropolitan areas.

5.2 Heterogeneity across Metropolitan Areas

Next, we explore metropolitan-level heterogeneity among the 2018 mandated metropolitan areas. HUD expanded the SAFMR mandate to 41 additional metros as of January 2025. Given this potential expansion, understanding the diverse effects and nuances across different metropolitan areas is vital. Each area has its own socioeconomic dynamics, housing market characteristics, demographic distributions, and institutional barriers within its PHAs.

Figure 7 illustrates the policy's standardized effectiveness at the metro level, revealing substantial variability in policy success across metropolitan areas. Certain areas—such as Monmouth-Ocean (NJ), North Port (FL), Harford (CT), Jackson (MS), San Antonio (TX), and Washington, DC—show markedly larger improvements for voucher recipients. By 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 runs counter to the policy's intended goals.

[26] A similar table for earlier demonstrations in other PHAs prior to 2018 is presented in Appendix Table D1.

Effect by Race Figure 8 presents the policy effectiveness by race in each metropolitan areas, indicating that overall standardized effects for White household-head voucher recipients are significantly greater (-0.1874) compared to those of Black households (-0.0493). These findings align with the broader patterns observed in earlier sections, where White households were already more likely to reside in lower-poverty neighborhoods prior to SAFMR implementation, and subsequently benefited more from the policy's introduction. By contrast, African-American households, who started out with less access to lower-poverty areas, show smaller reductions in poverty exposure and in some cases experience outcomes contrary to the policy's intended goals.

According to Panel (a) of Figure 8, this racial heterogeneity is especially pronounced in metropolitan areas where the policy proved less effective overall, such as Bergen-Passaic (NJ), Jacksonville (FL), Sacramento (CA), and Charlotte (NC). In these locations, positive SAFMR effects (i.e., movements to higher-poverty areas rather than lower-poverty ones) were primarily driven by African-American households.

5.3 Drivers of Heterogeneity in SAFMR Effectiveness

Understanding why the 2018 SAFMR mandate produced widely varying outcomes across metropolitan areas remains challenging. Several factors likely contribute to this heterogeneity, including overall rental market conditions, pre-existing racial and economic segregation, voucher-holder-specific market dynamics, the spatial organization of PHAs, and administrative constraints unique to each agency. While precisely disentangling these influences is difficult, we investigate how key pre-SAFMR metro-level characteristics correlate with policy effectiveness across the 15 mandated metropolitan areas.

Table 9 shows the correlations between the standardized effect of SAFMRs on reducing neighborhood poverty (where a negative value indicates a reduction) and HUD's selection criteria for 2018 mandate metros described in Section xx, which capture housing market conditions prior to SAFMR adoption: (1) total voucher counts, (2) voucher concentration in high-poverty areas, (3) the share of units priced above 110% of the metropolitan-wide FMR, and (4) overall rental vacancy rates. A key finding is that a higher pre-existing concentration

of vouchers in disadvantaged neighborhoods is strongly and negatively correlated with the standardized effect (Row (3)), implying that metropolitan areas where voucher holders were initially more clustered in low-income areas experienced greater poverty reductions once payment standards were recalibrated to ZIP-level metrics. This outcome may reflect how SAFMR, by increasing rental budgets for voucher holders, expands the range of lower-poverty neighborhoods they can move to.

In Rows (5) and (6), we also measure "excess poverty concentration" for each racial group, defined as the difference between the group's share in high-poverty neighborhoods and its share in the metropolitan area overall (see Appendix Table D4 for MSA-level values). As shown in Row (5), for African-American voucher recipients, a lower excess concentration in high-poverty areas prior to the mandate correlates with larger subsequent poverty reductions, underscoring the critical role of pre-SAFMR spatial segregation. By contrast, White households' concentration in high-poverty neighborhoods shows no discernible effect. Although fully examining the drivers behind these pre-SAFMR racial segregation patterns exceeds our scope, our findings suggest that pre-existing racial mobility constraints within metropolitan areas can shape policy effectiveness. Taken together, these results underscore how the initial distribution of voucher holders significantly influences SAFMR outcomes and highlight the importance of local context when scaling similar interventions.

6 Conclusion

Our analysis of the 2018 SAFMR mandate reveals a moderate shift in the distribution of Housing Choice Voucher recipients toward lower-poverty neighborhoods. This finding aligns with earlier demonstration studies, confirming that location-based rental subsidies can mitigate poverty exposure among voucher holders. However, effectiveness varies considerably both across metropolitan areas and by race—particularly between White and African-American households—echoing "voltage effect" concerns highlighted in List (2022) and Al-Ubaydli, Lai, and List (2023).

A major factor behind these uneven outcomes is the complex set of barriers facing exist-

ing voucher holders. Many struggle with uncertainty, myopic decision-making, strong social ties, and steep search costs (Bergman, Chan, and Kapor, 2020). In addition, persistent racial disparities in search costs and unit availability further hinder minority voucher recipients, contributing to the sizable gap in treatment effects we document. As a result, even when SAFMRs offer more generous subsidies in low-poverty areas, households facing higher mobility challenges or discrimination may be less able to benefit fully from these opportunities.

Our findings underscore the importance of tailoring horizontal expansion of SAFMRs—i.e., implementing the policy across multiple metropolitan areas—in ways that reflect local housing market conditions and institutional constraints. Pre-existing rental market characteristics, PHA administrative practices, and neighborhood-level segregation each play a critical role in shaping voucher outcomes. Ignoring these contextual factors can lead to uneven or muted results, as seen in several of the 15 metropolitan areas we examine (Banerjee et al., 2017; Pritchett and Sandefur, 2015).

Future research should investigate broader general-equilibrium effects on both voucher and non-voucher renters, including possible landlord responses to location-specific subsidies and overall shifts in neighborhood quality. A deeper understanding of landlords' decision-making—particularly regarding which applicants to accept and how rents are set—could prove instrumental in refining SAFMR policy design. Moreover, examining the sources of ongoing racial disparities in mobility outcomes (e.g., the extent to which racial homophily, discrimination, or other structural factors drive observed differences) stands as a critical next step. Finally, long-term evaluations of voucher recipients' neighborhood trajectories and well-being—especially once households relocate or exit the subsidy program—will help clarify whether the observed short-term gains translate into lasting improvements in opportunity and quality of life.

In summary, SAFMRs have shown promise in reducing poverty exposure for voucher holders, yet important challenges remain. Building on the lessons from these "15 independent experiments," future policy refinements and research should focus on the institutional, structural, and racial drivers of housing choice to maximize the program's broader effectiveness.

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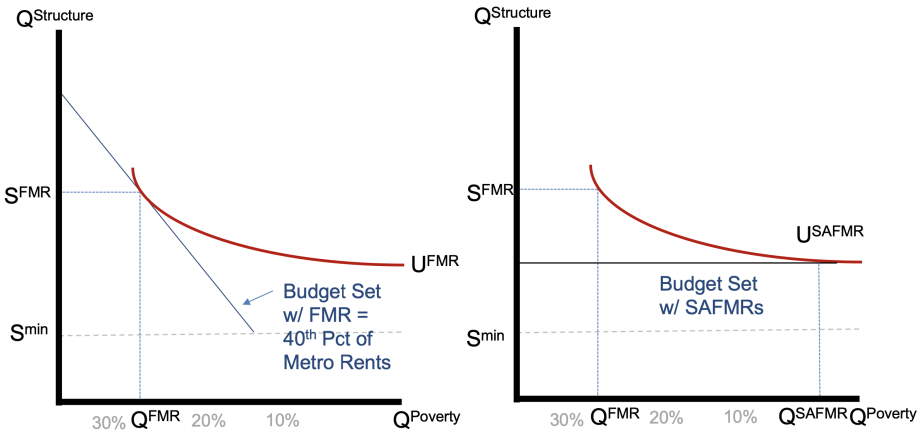
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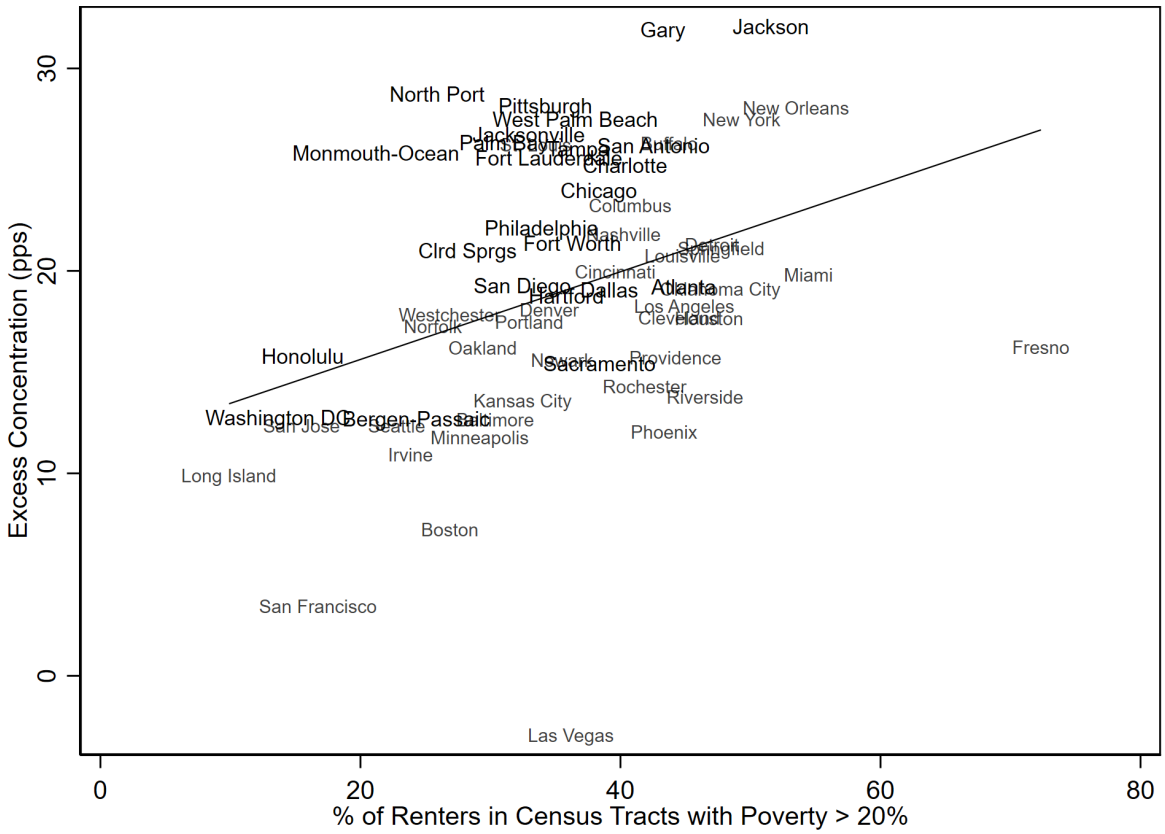
Figure 1: Conceptual Framework: Households' choices under FMRs versus SAFMRs

(a) Budget Constraint under FMRs (b) Budget Constraint under SAFMRs



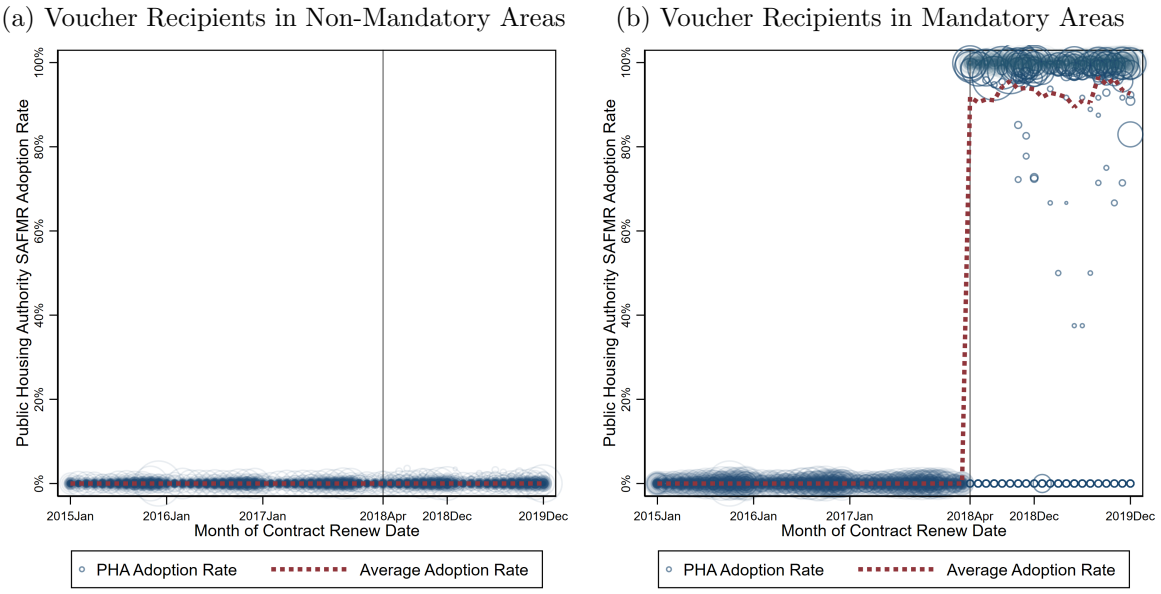
Notes: The horizontal axis represents neighborhood quality, while the vertical axis represents structure (unit) quality, with higher values indicating better quality. The straight lines illustrate the budget constraints under different payment standard schemes, and the utility indifference curves for voucher holders are also depicted. The notation $S_{\min}$ 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 SAFMR system, where the payment standard increases with neighborhood quality, and HUD requires a minimum unit quality to be maintained. Compared to the FMR system, SAFMR aims to improve neighborhood quality from Q_{FMR} to Q_{SAFMR} while ensuring a minimum structure (unit) quality standard is upheld.

Figure 2: Excess Poverty Concentration of Voucher Holders in the 50 Most Populous US Metropolitan Areas



Notes: The x-axis represents the percentage of all renters living in neighborhoods where the poverty rate exceeds 20% in the 50 largest U.S. metropolitan areas in 2017, based on the American Community Survey. The y-axis shows the difference, in percentage points, between the share of Housing Choice Voucher (HCV) recipients in these high-poverty neighborhoods and the share of all renters in the same metropolitan area. Metropolitan areas shown in black indicate those where the use of Small Area Fair Market Rents (SAFMRs) became mandatory in April 2018, while those in grey represent non-mandated metropolitan areas.

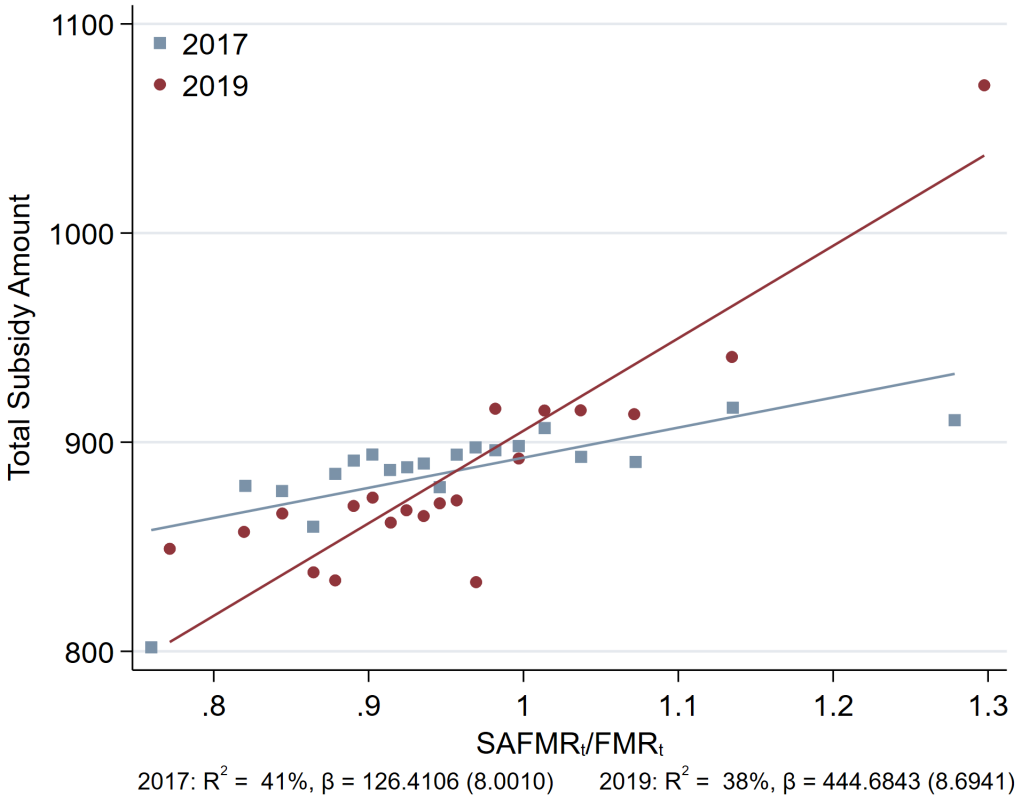
Figure 3: SAFMRs Adoption Rate by the Public Housing Authorities by Mandatory Status



Notes: The figures illustrate the SAFMRs adoption rate of each public housing authorities (PHAs) in the 50 most populous metropolitan areas by month. The x-axis for Panels (a) and (b) is by contract renewal date of voucher recipients. PHAs were required to use SAFMRs based payment standards for all first-time recipients after April 2018 whereas the contract renewal date after April 2018 for those with an prior allocation. The size of each circle reflects the relative number of housing vouchers allocated monthly by each PHA.

Figure 4: Housing Subsidy Amount and Zipcode-level Market Rent (2017 vs. 2019)

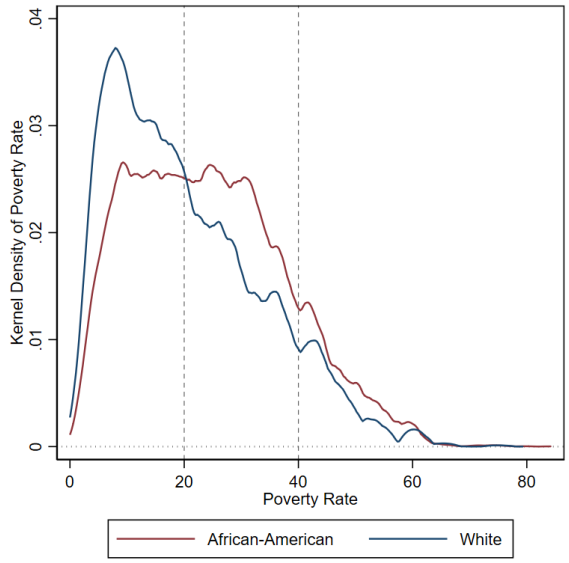
(a) All Existing 2017 vs. 2019



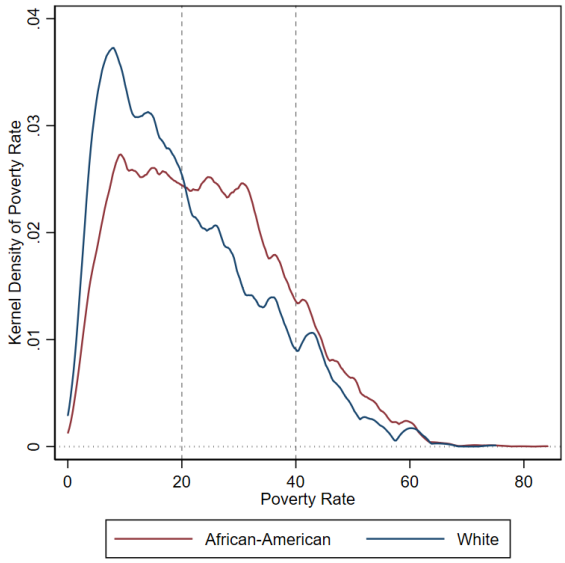
Notes: The plot compares the average subsidies between the same set of voucher holders appeared in 2017 and 2019, focusing solely on voucher recipient households that currently reside in the 15 mandatory metros. Each dot on the plot represents the mean value for one of the 20 quantiles of the ZIP code-level SAFMR/FMR distribution.

Figure 5: Surrounding Tract Poverty Rate by Race of Household Head

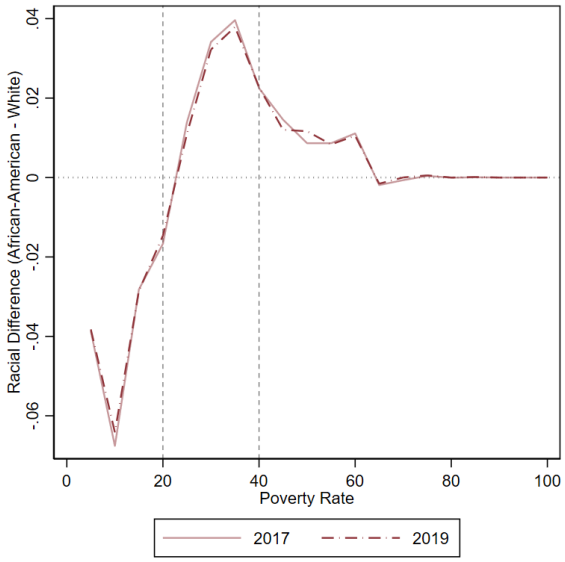
(a) 2017



(b) 2019



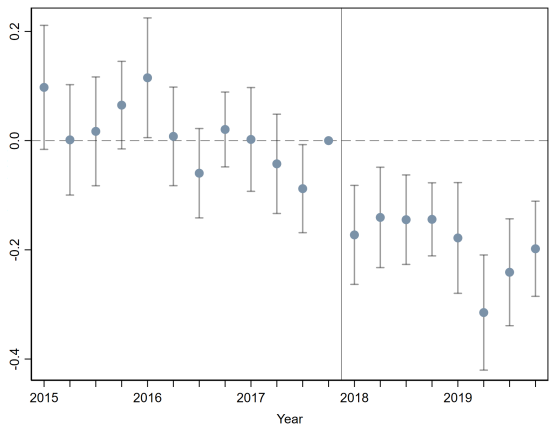
(c) Racial Gap



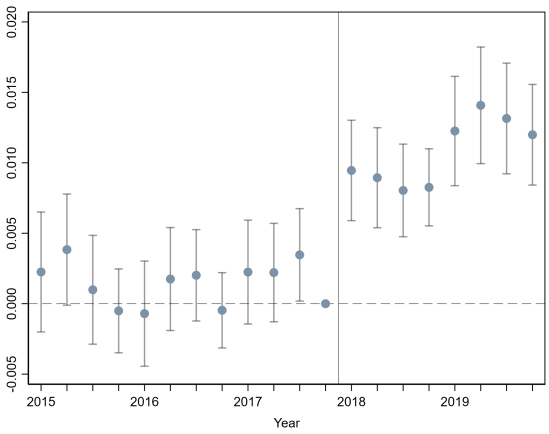
Notes: The figures show the distribution of all voucher holders in mandatory metropolitan areas in 2017 and 2019 by their surrounding census track poverty rate and the race of household head. Panel (a) shows the distribution (kernal density function) in 2017 and Panel (b) shows it in 2019. Panel (c) displays the racial gap in each surrounding tract poverty rate bin (5 pps) for year 2017 and 2019.

Figure 6: Effect of SAFMR Payment Standard on Voucher Holders' Surrounding Tract Poverty Exposure

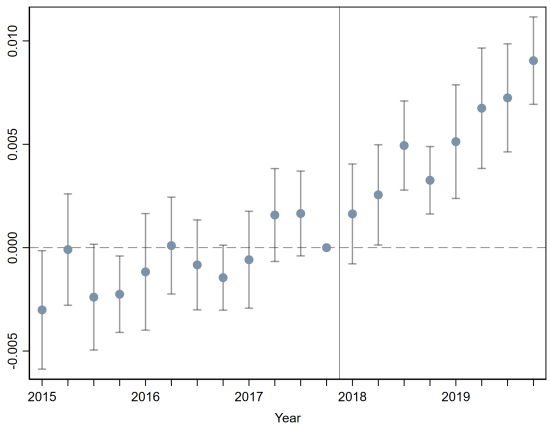
(a) Census Tract Poverty Rate



(b) Tract Poverty Rate <20%

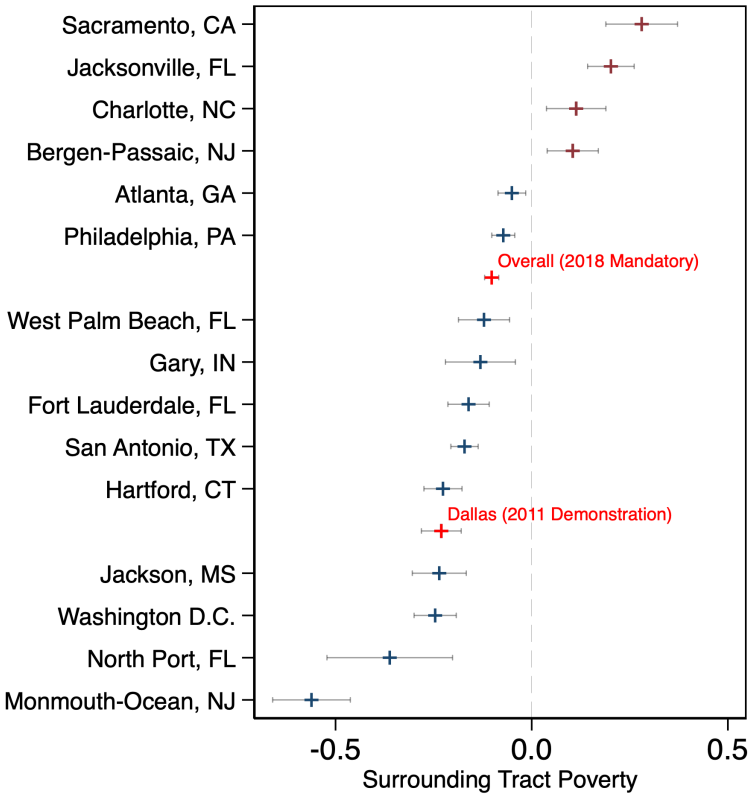


(c) Tract Poverty Rate <10%



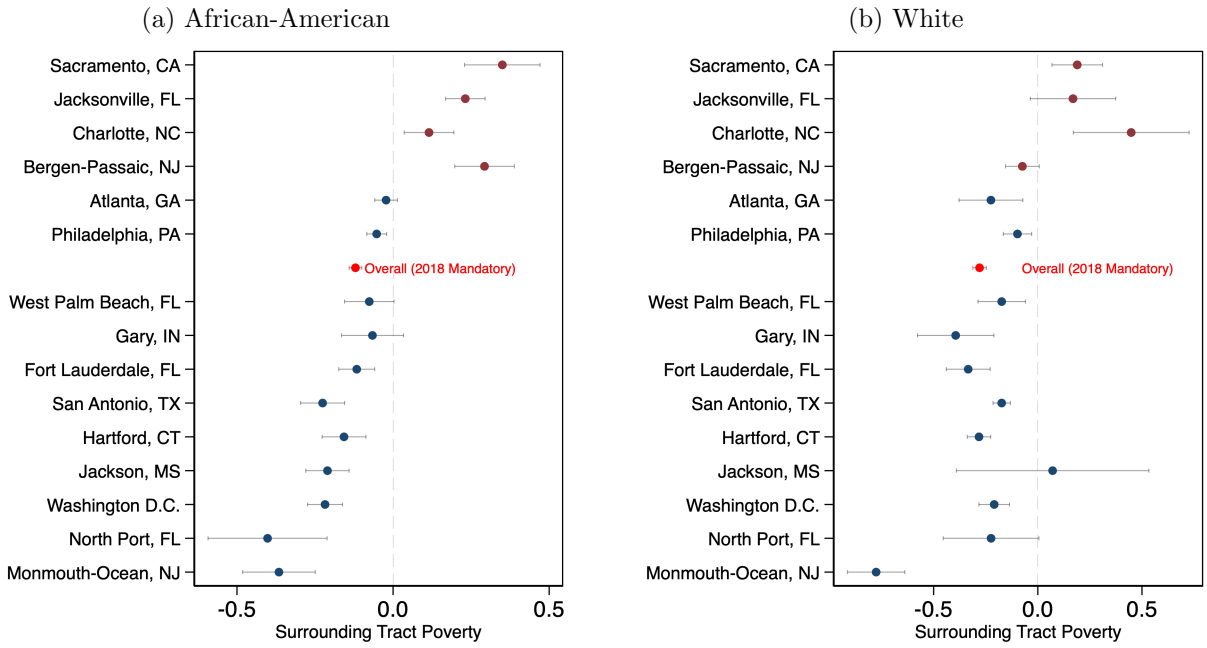
Notes: The figures display the quarterly event-study for existing voucher recipients on tract poverty exposure. The baseline is the fourth quarter of 2017 before mandate imposed and grey bars represents 90% confidence intervals based on county-PHA-contract renew time (year-month) clustered standards errors. Treatments are indicated by red dots for voucher holders in SAFMRs mandatory areas. The estimates control for county, contract renew time (year-month), and households fixed effects.

Figure 7: SAFMR Effects on Surrounding Tract Poverty Rates across metropolitan areas



Notes: This figure illustrates the heterogeneity in policy effectiveness across metropolitan areas. The control group for the 2011 Dallas demonstration consists of PHAs with similar attributes, including FMR levels, number of vouchers, and working-age population. These control groups exactly match those used in Dastrup et al. (2018). The control groups for each 2018 mandatory metropolitan areas comprise the 15 comparison metropolitan areas described in Section xx. The standardized effects are displayed in the figure, with point estimates presented in Table D2. A negative standardized effect indicates an improvement (i.e., a reduction in the poverty rate).

Figure 8: SAFMR Effects on Surrounding Tract Poverty Rates across metropolitan areas by Race of Household Head



Notes: This figure illustrates the heterogeneity in policy effectiveness across metropolitan areas by the race of the household head. The control group for the 2011 Dallas demonstration consists of PHAs with similar attributes, including FMR levels, number of vouchers, and working-age population, and exactly matches the control groups used in Dastrup et al. (2018). The control groups for the 2018 mandatory metropolitan areas comprise the 15 comparison metropolitan areas described in Section xx. Panel (a) reports the standardized effect and significance level for African American-headed voucher households, while Panel (b) reports the same for White-headed voucher households. The standardized effects are displayed in the figure, with point estimates presented in Table D3. A negative standardized effect indicates an improvement (i.e., a reduction in the poverty rate).

Table 1: Metropolitan Areas Selected by US Department of Housing and Urban Development for Mandatory SAFMRs Vouchers Starting in April 2018

	Voucher Count	Voucher Concentration	Unit Concentration	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 15 mandated metros used in our analysis, originally selected from 24 metros by HUD based on four criteria detailed in Columns (1) to (4). Column (1) shows the total number of voucher households in each metro. Column (2) measures the concentration rate of voucher holders in low-income census tracts. Column (3) represents the proportion of rental units in areas where Small Area Fair Market Rents (SAFMRs) exceed 110% of the metro Fair Market Rents (FMRs), calculated at the Zip Code Tabulation Areas (ZCTAs) level. Column (4) details the metro-level rental vacancy rate, indicating units vacant for rent relative to the total units available (vacant and renter-occupied). Out of the 24 HUD metros that met these criteria, nine were excluded from our analysis due to data inconsistencies or early adoption of SAFMR. For more information, see Appendix A.

Table 2: Descriptive Statistics of First-Time and Existing Voucher Recipients in SAFMRs-Mandatory Metropolitan Areas in 2017

Panel A: By First-Time and Existing Voucher Recipients

Mean	(1) First-Time Recipients (2017)	(2) Existing Recipients (2017)
Dependent Variables		
Census Tract Poverty Rate	24.1052	23.1230
<20% Poverty Tract	0.4379	0.4609
<10% Poverty Tract	0.1954	0.1943
Move Addresses When Renew Subsidy	-	0.1454
Voucher Recipients Demographics		
Black	0.6182	0.6722
Asian	0.0100	0.0192
Other Race	0.0144	0.0098
Hispanic	0.1738	0.1546
Female	0.7032	0.8465
Kids Present	0.4743	0.5850
Household Member w/ Disabilities	0.2755	0.2496
Age≤30 (Baseline)	0.2281	0.1866
Age 30-40	0.2420	0.2759
Age 40-50	0.1377	0.2145
Age 50-60	0.1998	0.1848
Age 60-70	0.1300	0.0888
Age>70	0.0625	0.0494
One Household Member (including head, baseline)	0.4168	0.2925
Two Household Members	0.2062	0.2166
Three Household Members	0.1458	0.1875
More than Three Household Members	0.2312	0.3034
Number of Households	6,116	171,929
N	6,116	175,556

Panel B: By African-American and White Headed Households

Mean	(1) African-American (2017)	(2) White (2017)	(3) Difference
Dependent Variables			
Census Tract Poverty Rate	24.4478	20.4037	-4.0441***
<20% Poverty Tract	0.4124	0.5652	0.1529***
<10% Poverty Tract	0.1600	0.2676	0.1075***
Female	0.8855	0.7688	-0.1166***
Age	41.96	48.59	6.63***
Kids Present	0.6476	0.4511	-0.1965***
Household Member w/ Disabilities	0.2221	0.3107	0.0886***
Adjusted Monthly Income	1,231	1,192	-39***
Average Moving Distance (in miles)	13.87	11.32	-2.55*
N	118,001	52,463	

Notes: Voucher recipients demographics variables are from the head of the households. Disability status includes whether the household head or any household member was disabled.

Table 3: Effect of SAFMR Payment Standard on Voucher Holders' Surrounding Tract Poverty Exposure

Dependent Variable	Poverty Rate	<20% Poverty	<10% Poverty
	(1)	(2)	(3)
SAFMR Payment Standard	-0.1834***	0.0091***	0.0061***
	(0.0197)	(0.0008)	(0.0005)
FEs	Year-Month	Year-Month	Year-Month
	County	County	County
	Households	Households	Households
Move Rate (2017)	14.54%	14.54%	14.54%
Treatment-on-Treated (TOT)	-1.2613***	0.0626***	0.0420***
Avg. Dependent Variable (2017)	23.1230	0.4609	0.1943
N	2,448,168	2,448,168	2,448,168

Notes: This table examines existing voucher holders who have been in the voucher program both before and after the implementation of SAFMRs. The independent variable is an indicator of whether households' payment standards are determined by SAFMRs. Columns (1) uses census tract-level poverty rates as dependent variables; Columns (2) uses a dummy variable that equals one if the census tract where the household is located has a poverty rate less than 20%; Columns (3) uses a dummy variable for tracts with less than 10% poverty. The results present OLS (Ordinary Least Squares) estimates. All estimates incorporate household fixed effects, along with fixed effects for year-month and county. Standard errors are clustered at the county-PHA contract renewal time (year-month) and in the parenthesis. (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

Table 4: Effect of SAFMR Payment Standard on Voucher Holders on Moving Address When Renewing Subsidy Contract by Prior Difference in Tract Poverty

Dependent Variable	Moving Address When Renewing Subsidy (0,1)		
	(1)	(2)	(3)
Sample	Overall	Initially Located in Lower Poverty Poverty<20%	Initially Located in Higher Poverty Poverty≥20%
SAFMR Payment Standard	-0.0048***	-0.0074***	-0.0025
	(0.0016)	(0.0019)	(0.0021)
Move Rate (2017)	14.54%	13.15%	15.73%
N	2,448,168	885,669	1,302,982

Notes: This table conducts a subsample analysis based on the 2017 initial locations of existing voucher recipients prior to SAFMRs implementation. The independent variable is an indicator of whether households' payment standards are determined by SAFMRs. The dependent variable is a dummy variable equal to one if households change locations from previous time periods. Subsamples are divided based on the poverty rate of the recipients' initial locations in 2017: Columns (2) focues on the tracts with poverty rates below 20%; Columns (3) focues on the tracts with poverty rates above 20%. All estimates use OLS and include household, year-month, and county fixed effects. Standard errors are clustered by county-PHA contract renewal time (year-month). Statistical significance is indicated by (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

Table 5: Effect of SAFMR Payment Standard on Voucher Holders' Surrounding Tract Poverty Exposure by the Race of Household Head

Dependent Variable	Poverty Rate		<20% Poverty	
	(1)	(2)	(3)	(4)
Variable	African-American	White	African-American	White
SAFMR Payment Standard	-0.1205***	-0.2794***	0.0080***	0.0100***
	(0.0245)	(0.0284)	(0.0009)	(0.0012)
FEs	Year-Month County Households	Year-Month County Households	Year-Month County Households	Year-Month County Households
Avg. Dependent Variable (2017)	24.4478	20.4037	0.4124	0.5652
N	1,413,125	922,359	1,413,125	922,359

Notes: The table examines existing voucher recipients who have been in the voucher program both before and after the implementation of SAFMRs, by the race of household head. The independent variable is an indicator of whether households' payment standards are determined by SAFMR. Columns (1) and (2) show the results of African-American and White headed households using census tract-level poverty rates as dependent variables; Columns (3) and (4) use a dummy variable that equals one if the census tract where the household is located has a poverty rate less than 20%. All estimates incorporate household fixed effects, along with fixed effects for year-month and county. Standard errors are clustered at the county-PHA contract renewal time (year-month) and in the parenthesis. (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

Table 6: Effect of SAFMR Payment Standard on Voucher Holders' Moving Address When Renewing Subsidy by the Race of Household Head

Dependent Variable	Moving Address When Renewing Subsidy (0,1)		
Sample	Overall	African-American	White
Variable	(1)	(2)	(3)
SAFMR Payment Standard	-0.0048***	-0.0044**	-0.0064***
	(0.0016)	(0.0021)	(0.0019)
FEs	Year-Month	Year-Month	Year-Month
	County	County	County
	Households	Households	Households
Move Rate (2017)	14.54%	16.07%	11.63%
N	2,448,168	1,413,125	922,359

Notes: This table examines existing voucher recipients who have been in the voucher program both before and after the implementation of SAFMRs, by the race of household head The independent variable is an indicator of whether households' payment standards are determined by SAFMRs. Columns (1) shows the overall results as indicated in previous table, and columns (2) and (3) show the results of African-American and White headed households. All estimates incorporate household fixed effects, along with fixed effects for year-month and county. Standard errors are clustered at the county-PHA contract renewal time (year-month) and in the parenthesis. (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

Table 7: Effect of SAFMR Payment Standard on Voucher Holders' Surrounding Tract Poverty Rate by the Race of Household Head and If School Age Kids Present

Sample			African-American		White	
Dependent Variable: Poverty Rate	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)
SAFMR Payment Standard	-0.1623***	-0.1811***	-0.1307***	-0.1120***	-0.2553***	-0.2777***
	(0.0366)	(0.0206)	(0.0451)	(0.0261)	(0.0635)	(0.0291)
FEs	Year-Month County Households	Year-Month County Households	Year-Month County Households	Year-Month County Households	Year-Month County Households	Year-Month County Households
Avg. Dependent Variable (2017)	23.0919	23.1312	23.7005	24.6771	21.2184	20.2611
N	443,697	2,004,470	306,480	1,106,644	122,723	799,636

Notes: This table examines existing voucher recipients who have been in the voucher program both before and after the implementation of SAFMRs, by the race of the household head, and if any school age kids (6-12) present in the households when they firstly appeared in the sample. School age kids are between age 6-12. The independent variable is an indicator of whether households' payment standards are determined by SAFMRs. Columns (1) shows the overall results without or with school age kids, and columns (3) and (4) show the results of African-American and columns (5) and (6) show the results of White headed households. All estimates incorporate household fixed effects, along with fixed effects for year-month and county. Standard errors are clustered at the county-PHA contract renewal time (year-month) and in the parenthesis. (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

Table 8: Comparing SAFMR 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 Metros (control)		Mandatory Metros (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 estimates of the effect of transitioning from FMRs to SAFMRs on voucher holders' neighborhood quality. 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 metros 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.

Table 9: Correlation of Policy Estimates with Pre-SAFMR Metropolitan Area Characteristics

	Standardized Effect of Poverty Reduction	Correlation Coefficient	P-Value
(1)	Voucher Count	0.0516	0.8552
(2)	Voucher Concentration in Concentrated Low Income Areas	-0.5646**	0.0283
(3)	% All Units in SAFMR≥110%FMR	-0.2924	0.2903
(4)	Rental Unit Vacancy Rate	0.0087	0.9754
(5)	African-American Voucher Holders' Excess Concentration in High-Poverty Areas	0.4783*	0.0713
(6)	White Voucher Holders Excess Concentration in High-Poverty Areas	-0.1620	0.5641

Notes: The table displays the correlation coefficients of the metropolitan-level standardized effect of poverty reduction among existing voucher holders, regressed on pre-mandate metropolitan characteristics for 15 metropolitan areas. Significance levels are denoted by * ($p < 0.1$), ** ($p < 0.05$), and *** ($p < 0.01$). Rows (1) to (4) report the variables that HUD used when selecting these mandatory metropolitan areas in April 2018. A negative correlation coefficient indicates that higher values of a given metropolitan characteristic are associated with greater poverty reduction (i.e., an improvement). In rows (5) and (6), the "African-American (or White) voucher holder concentration in high-poverty areas" is defined as the difference between the share of that racial group in census tracts with poverty rates above 20% and the share of all voucher holders in such high-poverty tracts.

Online Appendices

A Data Appendix

A.1 Sample Construction

We start with a sample of household head between 2009 to 2020 (N=33.33 million) from the PIC data we received. We dropped any voucher holders of home ownership voucher and project-based voucher (N=0.75 million), and dropped other programs that are not in the program 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 data base (N=1.12 million). This leaves us a sample of 14.25 million observations before we merge and restrict.

We merged the raw PIC data as well as the fair market rent data to identify which households using the SAFMRs as their payment standard (if effective FMRs equal to SAFMRs), and 1.8% of sample without such information and excluded. Then we futher restricted sample as our selected control and treatment metropolitan areas (N=5.38 million).

For poverty rate, we use their poverty rate observed during year 2012-2017 since they are using 2010 Census poverty rate consistently. Only 598 observations does not have this measurement hence we use their first observed poverty rate as the poverty rate measurements. For household-level demographics control variables, we use their first-observed attributes. Only 888 observations have at least one of the variables missing and thus are excluded. We constructed a repeated cross-section sample at household level and use the year-month component of the date variable hereafter ("effective date") in the PIC data to identify the contract start time for first-time recipients and contract renew time for existing ones (Collinson and Ganong, 2018). Contract date before 2014 and after 2019 were also dropped, and this leaves us a sample of 3.37 million.

We only drop the voucher households with the account type equals to 6, to exclude impacts of attrition.[27][28] We identify the first-time recipients as the voucher holders coded as 'new admission' and are the first observations of each household sample, and the remaining observations are existing voucher recipients. This leaves us a final sample of 3.19 million observations from 2014 to 2019 since we need 2014 data to decide if the household moved compared with previous year's address. During 2015 to 2019, we have 2,649,077 observations. The existing recipients sample is 95% and first-time recipients are 5% in total. In regression, 3.6% of the existing sample observations are dropped because of singleton observations. There are 270,492 households in the SAFMR mandatory metropolitan areas.

[27] 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%).

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

A.2 HUD's Mandated metropolitan areas Selection Criteria

The four selection benchmarks detailed in Columns (1) to (4) of Table 1 are calculated as listed below. We downloaded HUD's selection benchmarks from HUD's website, and merged with the rental units vacancy rate from Social Explorer 5-Year American Community Survey (2013-2009). The first three criteria information in Table 1 is directly downloaded from HUD (Initial Proposed Selection Tool[29]) Besides, one additional criterion (the last vacancy rate requirement) as well as require the voucher concentration ratio's numerator are added by HUD for the final rule due to public comments.[30] We calculate each criteria in the following ways:

1. Total number of voucher households in the metro.

2. Voucher Concentration (census track level measure) 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 the 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 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. Unit Concentration (Zip Code Tabulation Areas level measure) is defined as number of units in ZCTAs with SAFMRs above 110% Metro FMRs divided by the number of all renter units in that ZCTA.

4. Rental Units Vacancy Rate (metro level measure) is defined as the number of vacant for rent units divided by sum of the number of vacant for rent units, the number of renter-occupied units, and the number of rented but not occupied units. We use American Community Survey 5 Year estimates for 2013 to 2009 from Social Explorer to determine the metropolitan level rental units vacancy rate. Unlike final rule's recommendation[31], we directly use 5-year estimates based on the feedback from HUD. More importantly, 1-year ACS is less representative and only cover a subset of for all tracts in the metro areas.

Though HUD the final rule 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: almost all metros' voucher holders are concentrated in high poverty areas (see Figure 2) and there is no such requirement in the initial proposed selection tool.[32] Thus, we combine the three

[29] See SAFMR Proposed Rule Area Selection Tool

[30] See Kep Aspects of the Final Rule

[31] Vacancy rate is calculated from the 3 most current 1-year ACS estimates and takes average.

[32] See SAFMR Proposed Rule Area Selection Tool

initial selection parameters as well as the rental unit vacancy rate as our parameters when we selecting the comparison metros.

A.3 Selection of 15 Mandated Metro Used in Our Analysis

Out of 24 HUD metros that met these criteria, nine were excluded from our analysis for various reasons.

- First, five HUD metros are lack of 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, pre-treated areas and metros are very close to the pre-treated areas were also not included. Chicago-Joliet-Naperville, IL HUD Metro FMR Area, Dallas-Plano-Irving, TX Metro Division and Fort Worth-Arlington, TX HUD Metro FMR Area are excluded due to 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 due to the same reason.

- Third, any metros area that opted out from the mandatory adoption is excluded, like participating in the Move-To-Work program that allows housing authority-level individual 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 Small Area Fair Market Rent (SAFMR) for the zip codes associated with the identified areas.[33] In other words, Pittsburgh only has two payment standards and thus we also exclude Pittsburgh, PA HUD Metro FMR Area in the treatment sample.

A.4 Definition of Neighborhood Poverty Rates

In our analysis, we use the poverty rate variable directly from the HUD's original administrative data, aligning with HUD's standards for decision-making. Specifically, we define neighborhood poverty rates as the percentage of the population below the poverty level in census tracts, using the Census 2010 designation for tracts from 2012 onward. This approach excludes any spillover effects from voucher recipients on neighborhood poverty; we employ the 2010 Census tract poverty rates for the years 2012 to 2017 in our sample. For tracts without any voucher holders prior to 2017 (6,928 out of 47,635 tracts), we use the

[33]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.

first observed non-missing tract-level poverty rate as their poverty level for 2011 to 2021. In the HUD's original administrative data, a very small number of household-year observations (6,340) do not have an associated poverty rate.

A.5 Definition of Moving

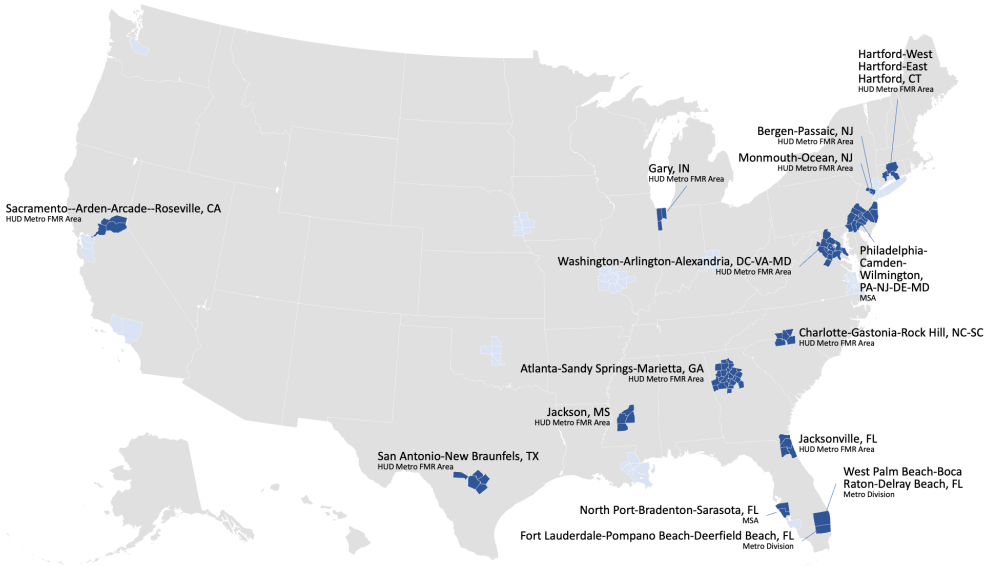
We compare the information on each household address, and if it is different from the last observed address (sorted by contract start/renew time first), we code it as 'moved' household. It means households were only observed if moved *in* current address when renewing their subsidy. When calculating move rate, households who moved more than once during a calendar year are counted as one to avoid double counting.

A.6 Definition of SAFMR-based Payment Standard

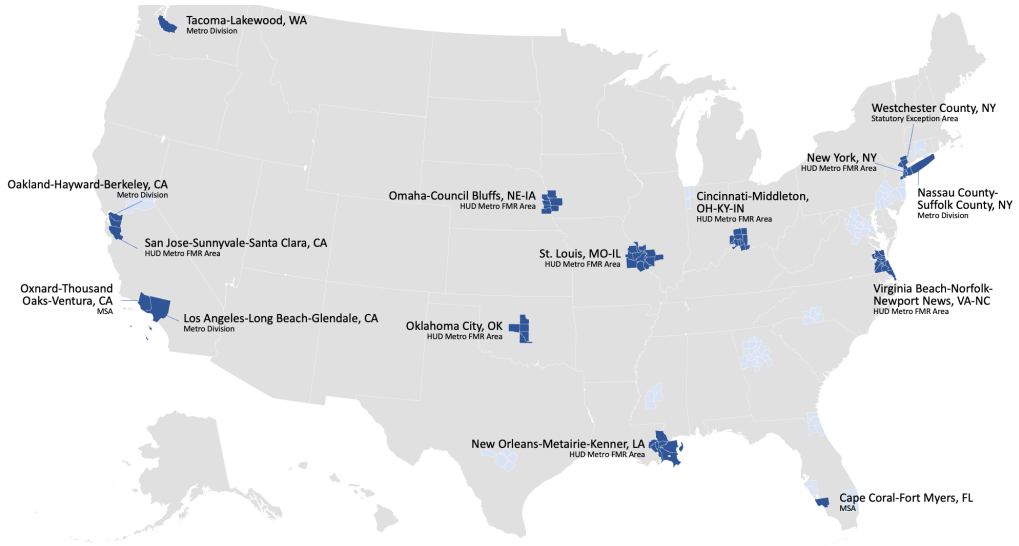
We compare the effective fair market rent (EFMR) at the household level with the SAFMR and the FMR. This information is from the data we received from HUD and we merge it using household identification number to the PIC data sets. If it is equal to SAFMR, we define the households that are using SAFMR based payment standard for their voucher subsidy. Otherwise, households are still using the metro-wide FMR based payment standard. This method directly identifies the households if they receive the SAFMR-based voucher, and avoids additional issues, such as the local subsidy payment amount, set as 90% to 110% of SAFMR or FMR by the local PHAs.

Figure A1: Mandatory Metros and Comparison Metros in the Sample

(a) 15 Mandatory Metros

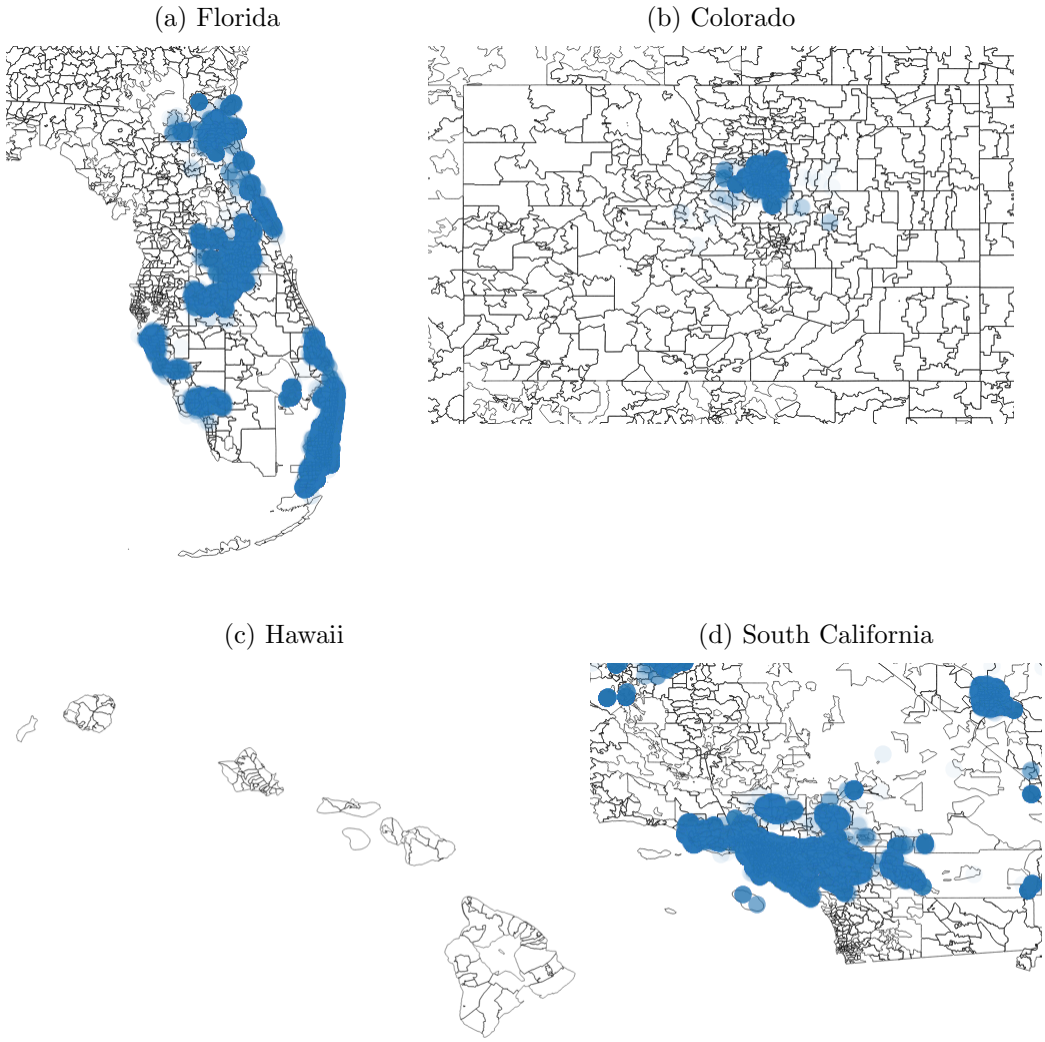


(b) 15 Comparison Metros



Notes: Panel (a) displays the 15 mandatory metros in our mandatory group sample. Panel (b) displays the 15 comparison metros in our sample group for comparison. The comparison metros were chosen by relaxing the criteria and including metros that met the criteria but was not in the final list.

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 that are directly from the uncleaned raw data we received.

Table A1: Comparison Metropolitan Areas Who Narrowly Missed being Selected by US Department of Housing and Urban Development for Mandatory SAFMR Vouchers Designation in 2018

	Voucher Count	Voucher Concentration	Unit Concentration	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 presents how the comparison metros are selected, with HUD's selection benchmarks detailed in Columns (1) to (4). Column (1) shows the total number of voucher households in each metro. Column (2) measures the concentration rate of voucher holders in low-income census tracts. Column (3) represents the proportion of rental units in areas where Small Area Fair Market Rents (SAFMRs) exceed 110% of the metro Fair Market Rents (FMRs), calculated at the Zip Code Tabulation Areas (ZCTAs) level. Column (4) details the metro-level rental vacancy rate, indicating units vacant for rent relative to the total units available (vacant and renter-occupied). Panels A to D list the comparison metros, each relaxing one of the four criteria. Panel E lists four metros that originally met HUD's standards but were not selected for the HUD's Mandatory Metro list.

B Alternative Regression Specifications

Instrumental Variable To address endogeneity in the use of the SAFMRs payment standard, that different Public Housing Authorities (PHAs) have slower or faster compliance, voucher holders carry voucher from a mandatory PHAs to an non-mandatory PHAs, as well as the plausible exogenous of the contract start time that recipients only recalibrate the payment standard when they start or renew the leasing contract. For first-time voucher recipients, we leverage the 1-month lagged SAFMRs compliance rate of the PHA administering their voucher. For the existing voucher recipients, we constructed a 'leave-one-out' compliance rate that using the current month's compliance rate but remove the voucher recipients themselves to exclude any left endogeneity concerns. Specifically, our first-stage regression is set up for household i residing in PHA p, counties c (nested in metropolitan area m), in year-month t,

$$\mathbb{I}(\text{PayStand=SAFMR})_{i,p,m,t} = \alpha + \gamma \text{PHA Compliance Rate}_{-i,p,m,t} + \lambda \mathbf{X}'_{i,t} + \lambda_i + \delta_c + \zeta_t + \epsilon_{i,p,m,t}$$

where an important intuition for constructing the instrument variable is that the voucher recipients who carry their voucher from a compliance PHA to a non-SAFMR-mandatory metropolitan areas will not receive the SAFMR as their payment standard. The determinate of the SAFMRs based payment standards are plausible exogenous and should be only decided by their administrating housing authorities. For existing voucher holders, the households fixed effect is controlled instead of household demographics control variables.

Table B1: Effect of SAFMRs Payment Standard on Census Tract Poverty Exposure of Existing Voucher Holders

Panel A: IV Regression

Dependent Variable	Poverty Rate	<20% Poverty	<10% Poverty
	(1)	(2)	(3)
SAFMR Payment Stand.	-0.1799***	0.0090***	0.0060***
	(0.0197)	(0.0008)	(0.0005)
FEs	Year-Month	Year-Month	Year-Month
	County	County	County
	Households	Households	Households
Avg. Dependent Variable (2017)	23.1230	0.4609	0.1943
N	2,448,168	2,448,168	2,448,168

Panel B: First-Stage IV Regression

Dependent Variable	Poverty Rate	<20% Poverty	<10% Poverty
	(1)	(2)	(3)
Variable	2SLS	2SLS	2SLS
1^{st} Stage: Adoption Rate$_{-i,p,c,t}$	0.9868***	0.9868***	0.9868***
	(0.0004)	(0.0004)	(0.0004)
1^{st} Stage K-P Wald rk F statistic	7,812,237	7,812,237	7,812,237
N	2,448,168	2,448,168	2,448,168

Notes: This table examines existing voucher holders who have been in the voucher program both before and after the implementation of SAFMRs. The independent variable is an indicator of whether households' payment standards are determined by SAFMRs. Columns (1) uses census tract-level poverty rates as dependent variables; Columns (2) uses a dummy variable that equals one if the census tract where the household is located has a poverty rate less than 20%; Columns (3) uses a dummy variable for tracts with less than 10% poverty. 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. All estimates incorporate household fixed effects, along with fixed effects for year-month and county. Standard errors are clustered at the county-PHA contract renewal time (year-month) and in the parenthesis. (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

Table B2: Effect of SAFMRs Payment Standard on Census Tract Poverty Exposure: Alternative Comparison Metropolitan Areas

Panel A: Alternative Comparison Metropolitan Areas

Dependent Variable	Poverty Rate	<20% Poverty	<10% Poverty
Variable	(1)	(2)	(3)
SAFMR Payment Standard	-0.0773***	0.0057***	0.0041***
	(0.0209)	(0.0008)	(0.0006)
FEs	Year-Month	Year-Month	Year-Month
	County	County	County
	Households	Households	Households
Avg. Dependent Variable (2017)	23.1230	0.4609	0.1943
N	2,022,107	2,022,107	2,022,107

Panel B: All Available Metropolitan Areas as Comparison Group

Dependent Variable	Poverty Rate	<20% Poverty	<10% Poverty
Variable	(1)	(2)	(3)
mandsafmr_alt	-0.1294***	0.0067***	0.0046***
	(0.0181)	(0.0007)	(0.0005)
FEs	Year-Month	Year-Month	Year-Month
	County	County	County
	Households	Households	Households
Avg. Dependent Variable (2017)	23.1230	0.4609	0.1943
N	5,504,548	5,504,548	5,504,548

Notes: This table examines effect of SAFMR payment standard voucher holders' surrounding tract poverty exposure using alternative comparison metropolitan areas. Panel A uses the comparison metropolitan areas as showed in Ellen, O'Regan, and Strochak (2024) and Panel B uses all available metropolitan areas as our control groups. The independent variable is an indicator of whether households' payment standards are determined by SAFMRs. Columns (1) uses census tract-level poverty rates as dependent variables; Columns (2) uses a dummy variable that equals one if the census tract where the household is located has a poverty rate less than 20%; Columns (3) uses a dummy variable for tracts with less than 10% poverty. All estimates incorporate household demographics control variables or household fixed effects, along with fixed effects for year-month and county. Standard errors are clustered at the county-PHA contract renewal time (year-month) and in the parenthesis. (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

C Effect on First Time Voucher Holders

Identification Strategy In this section, we focus on first-time voucher recipients who are first appeared in the data sets. Because they typically face long waiting periods before entering the Housing Choice Voucher program and due to high uncertainties of acceptance dates, the timing of their admission is effectively decoupled from PHAs' decisions on whether and when to implement SAFMR payment standards. For household i residing in PHA p,counties c (nested in metropolitan area m), in year-month $t \in \{\text{Jan 2015, Dec 2019}\}$, our twoway fixed effects estimates are identified as follow:

$$Y_{i,p,m,t} = \alpha + \beta \mathbb{I}(\text{PayStand=SAFMR})_{i,p,m,t} + \lambda \mathbf{X}'_{i,t} + \delta_c + \zeta_t + \epsilon_{i,p,m,t} \tag{2}$$

Here, $\mathbb{I}(\text{PayStand=SAFMR})_{i,p,m,t}$ indicates whether the household's voucher subsidy is determined under SAFMRs. We include socio-demographic controls $\mathbf{X}'_{i,t}$, year-month fixed effects ζ_t, and county fixed effects δ_c. The resulting variation allows us to compare first-time recipients in the same county, with and without SAFMR-based vouchers, holding constant local conditions. We focus on neighborhood poverty rates measured with 2010 Census data, mitigating concerns about endogenous neighborhood composition changes driven by the voucher holders themselves. Standard errors are clustered at the county-PHA-year-month level.

Results We focus on the initial poverty exposure of recipients who were first allocated a housing voucher. Although only 5% of the sample annually consists of new voucher holders (i.e., individuals entering the program for the first time in a given month-year), the initial placement records of these recipients provide the most straightforward sample, as their subsidy receipt typically requires relocation from their pre-voucher locations. In PHAs subject to the SAFMR mandate after April 2018, this relocation is likely to use SAFMR as the payment standard, since HUD required PHAs to uniformly apply the SAFMR payment standard for all first-time recipients.[34]

Table C1 reports estimates of the impact of using SAFMR payment standards on the poverty exposure of first-time voucher recipients. The implementation of SAFMR payment standards appears to significantly lower the poverty exposure of these recipients, though the effects are non-linear. Column (1) shows that the average tract poverty rate decreased by 0.70 percentage points (pps), reflecting a 3.0% reduction based on the 2017 average of 24.1%. Column (2) shows that the likelihood of living in a tract with less than 20% poverty increased by 2.1 ppt (4.8%). Notably, this increase is largely driven by a greater likelihood of residing in tracts with less than 10% poverty, which rose by 3.11 pps (16%).

First-time voucher holders, who are typically required to relocate from their pre-voucher locations upon subsidy receipt, experience substantial reductions in poverty exposure. This is because the new payment scheme provides stronger financial incentives for recipients to move to higher-rent, lower-poverty areas compared to the prior FMR system.

[34] Ellen, O'Regan, and Strochak (2024) focuses on the lease-up rate of first-time voucher holders.

Table C1: Effect of SAFMR Payment Standard on Initial Census Tract Poverty Exposure of First-Time Voucher Recipients

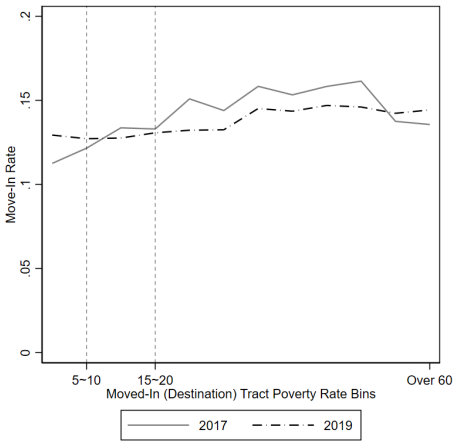
Dependent Variable	Poverty Rate	<20% Poverty	<10% Poverty
Variable	(1)	(2)	(3)
SAFMR Payment Standard	-0.6972***	0.0210**	0.0311***
	(0.2637)	(0.0099)	(0.0059)
FEs	Year-Month	Year-Month	Year-Month
	County	County	County
Controls	Demographics	Demographics	Demographics
Avg. Dependent Variable (2017)	24.1052	0.4379	0.1954
N	109,055	109,055	109,055

Notes: This table examines new voucher recipients who appear in the HUD administrative data for the first time and were not included in the data after the first year. The independent variable is an indicator of whether households' payment standards are determined by SAFMRs. Columns (1) uses census tract-level poverty rates as dependent variables; Columns (2) uses a dummy variable that equals one if the census tract where the household is located has a poverty rate less than 20%; Columns (3) uses a dummy variable for tracts with less than 10% poverty. The results present OLS (Ordinary Least Squares) estimates. All estimates incorporate socio-demographic controls, along with fixed effects for year-month and county. Standard errors are clustered at the county-PHA-contract start time (year-month) and in the parenthesis. (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

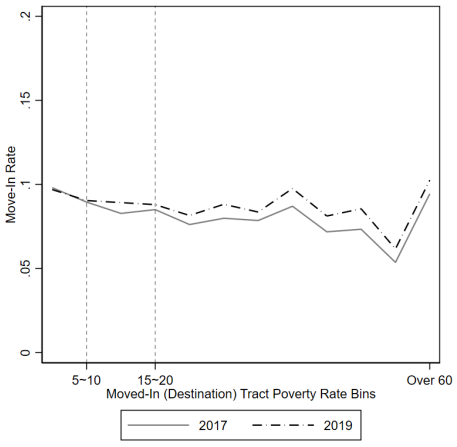
D Auxillary Tables

Figure D1: Move Rate by Surrounding Tract Poverty Rate

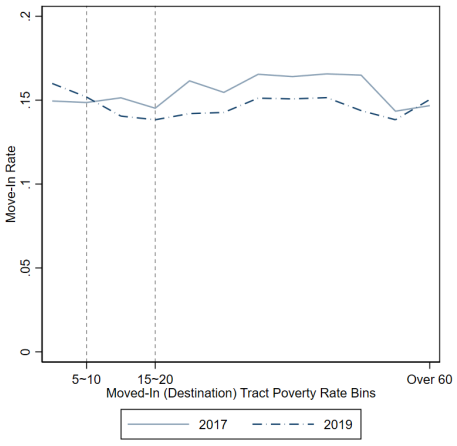
(a) Overall: Mandatory Metros



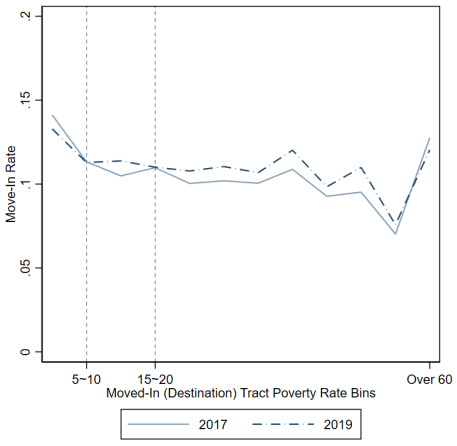
(b) Overall: Comparison Metros



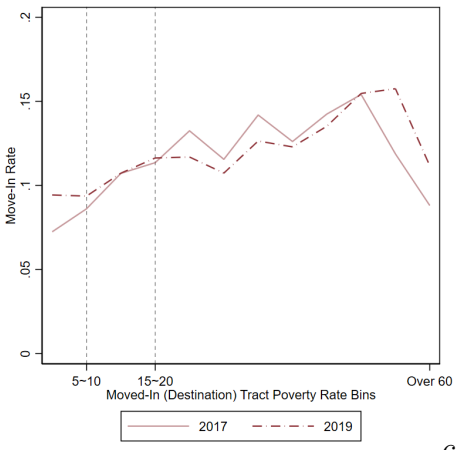
(c) African-American: Mandatory Metros



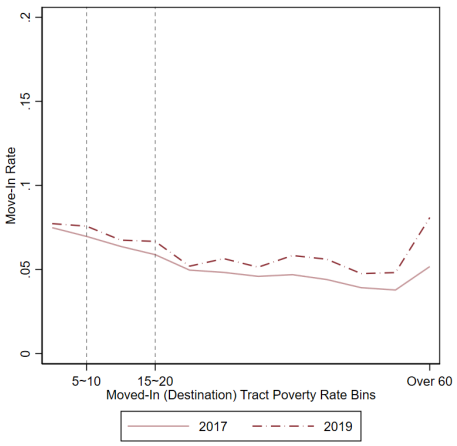
(d) African-American: Comparison Metros



(e) White: Mandatory Metros



(f) White: Comparison Metros



Notes: The figures show the move rate by each surrounding tract poverty rate bin (5 pps) for year 2017 and 2019.

Table D1: SAFMR Demonstrations

	Diff-in-Diff (ITT)	Move Rate	Diff-in-Diff (TOT) (2)/(3)	Standardized effect (3)/SD	Significance level
	(1)	(2)	(3)	(4)	(5)
2010-2014					
Chattanooga Housing Authority	-0.5871	12.44%	-4.7210	-0.3482	***
Housing Authority of Cook County	-0.4620	15.05%	-3.0698	-0.2277	***
City of Long Beach Housing Authority	-1.1085	9.93%	-11.1650	-0.8852	***
Town of Mamaroneck Housing Authority	-0.9550	7.00%	-13.6509	-1.4187	***
2009-2013					
Housing Authority of Plano	1.7088	13.74%	12.4376	0.9863	***

Notes: The table presents the treatment effects on the surrounding poverty rates of voucher holders in demonstration PHAs before the 2018 mandatory phase (excluding Laredo Housing Authorities (TX011), where no observations are available in our administrative data), using the same specification as in Section 3.3. Control groups for each demonstration PHA consist of PHAs with similar attributes (downloaded from Dastrup et al. (2018)) —such as FMR level, number of vouchers, and working-age population—following the approach in Dastrup et al. (2018). The Intention-to-Treat (ITT) estimate measures the average effect of introducing SAFMR payment standards to voucher recipients, using the same regression as our main specifications. The Treatment-on-Treated (TOT) estimate for existing voucher holders is obtained by dividing the ITT effect (Column (4)) by the move rate (Column (5)). Finally, the standardized effect is the TOT estimate divided by the standard deviation of the poverty rate for all Census tracts in each metropolitan area, where a negative value indicates a reduction in poverty.

Table D2: SAFMR Effects on Surrounding Tract Poverty Rates across metropolitan areas

	Effect of SAFMR Payment Standard on Voucher Holders' Surrounding Tract Poverty Rate				
	Diff-in-Diff (ITT)	Move Rate	Diff-in-Diff (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)	-0.1834	14.54%	-1.2616	-0.1020	***
Panel C. 2018 Mandatory metropolitan areas Heterogeneity					
Atlanta-Sandy Springs-Marietta, GA HUD Metro FMR Area	-0.0982	15.61%	-0.6290	-0.0506	**
Bergen-Passaic, NJ HUD Metro FMR Area	0.1022	8.35%	1.2243	0.1046	***
Charlotte-Gastonia-Rock Hill, NC-SC HUD Metro FMR Area	0.1793	12.87%	1.3930	0.1134	**
Fort Lauderdale-Pompano Beach-Deerfield Beach, FL Metro Division	-0.3600	22.30%	-1.6146	-0.1609	***
Gary, IN HUD Metro FMR Area	-0.2573	12.05%	-2.1352	-0.1307	**
Hartford-West Hartford-East Hartford, CT HUD Metro FMR Area	-0.4866	14.78%	-3.2924	-0.2261	***
Jackson, MS HUD Metro FMR Area	-0.4918	13.68%	-3.5945	-0.2355	***
Jacksonville, FL HUD Metro FMR Area	0.4108	17.68%	2.3231	0.2019	***
Monmouth-Ocean, NJ HUD Metro FMR Area	-0.4821	10.04%	-4.8022	-0.5612	***
North Port-Bradenton-Sarasota, FL MSA	-0.4686	13.58%	-3.4505	-0.3618	***
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD MSA	-0.1373	13.86%	-0.9909	-0.0724	***
Sacramento–Arden-Arcade–Roseville, CA HUD Metro FMR Area	0.2841	8.83%	3.2185	0.2804	***
San Antonio-New Braunfels, TX HUD Metro FMR Area	-0.5288	23.81%	-2.2212	-0.1712	***
Washington-Arlington-Alexandria, DC-VA-MD HUD Metro FMR Area	-0.2837	13.05%	-2.1734	-0.2461	***
West Palm Beach-Boca Raton-Delray Beach, FL Metro Division	-0.2596	19.15%	-1.3558	-0.1216	***

Notes: The table displays heterogeneity estimates of existing voucher holders by Dallas public housing authority before the 2018 mandatory, and each SAFMRs mandatory metropolitan area (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). 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). Control groups for mandatory metropolitan areas are the selected 15 comparison metropolitan areas. The Intention-to-Treat (ITT) effects estimates the average effect of offering the SAFMRs payment standard on voucher recipients, using the same regression as our main specifications. The Treatment-on-Treated (TOT) effects of existing voucher holders are the ITT effects (column (4)) divided by the move rate (column (5)), which is the percent of existing voucher holders change address when renew subsidy in one year before the SAFMR (2010 for Dallas, 2017 for mandatory adoption), considering the policy change does not largely impact on the move rate in aggregate. The standardized effects are the TOT effects divided by the standard deviations of poverty rate for all census tracts in each metropolitan areas, where negative indicates an improvement.

Table D3: SAFMR Effects on Surrounding Tract Poverty Rates across metropolitan areas by Race of Household Head

Metropolitan Areas	Total	% African American	African American		White	
	(1)	(2)	(3) Standardized Effect	(4) Significance	(5) Standardized Effect	(6) Significance
2015–2019						
Overall	166,888	69.03%	-0.0493	***	-0.1874	***
Atlanta-Sandy Springs-Marietta, GA HUD Metro FMR Area	25,774	95.44%	-0.0224		-0.2249	**
Bergen–Passaic, NJ	10,116	33.21%	0.2929	***	-0.0741	
Charlotte–Gastonia–Rock Hill, NC–SC	5,653	88.36%	0.1151	**	0.4483	
Fort Lauderdale-Pompano Beach-Deerfield Beach, FL Metro Division	10,495	81.17%	-0.1164	***	-0.3340	***
Gary, IN HUD Metro FMR Area	3,234	85.37%	-0.0661		-0.3941	***
Hartford-West Hartford-East Hartford, CT HUD Metro FMR Area	12,059	31.11%	-0.1572	***	-0.2821	***
Jackson, MS HUD Metro FMR Area	4,359	98.00%	-0.2102	***	0.0712	
Jacksonville, FL	6,337	85.89%	0.2313	***	0.1690	
Monmouth-Ocean, NJ HUD Metro FMR Area	7,545	34.29%	-0.3656	***	-0.7759	***
North Port-Bradenton-Sarasota, FL MSA	2,512	62.54%	-0.4020	***	-0.2243	
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD MSA	27,232	72.67%	-0.0526	***	-0.0975	**
Sacramento–Arden–Arcade–Roseville, CA	8,891	51.42%	0.3499	***	0.1893	**
San Antonio-New Braunfels, TX HUD Metro FMR Area	9,114	24.22%	-0.2257	***	-0.1733	***
Washington-Arlington-Alexandria, DC-VA-MD HUD Metro FMR Area	27,892	80.64%	-0.2180	***	-0.2093	***
West Palm Beach-Boca Raton-Delray Beach, FL Metro Division	5,675	75.59%	-0.0762		-0.1732	

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

Table D4: Percentage of Voucher Recipients in High Poverty Areas

	(1) % in Above 20% Poverty Areas	(2) Excess Concentration of African-American Voucher Holders	(3) Excess Concentration of White Voucher Holders
Overall	53.76%	4.85%	-10.35%
Atlanta-Sandy Springs-Marietta, GA HUD Metro FMR Area	66.89%	0.62%	-14.77%
Bergen-Passaic, NJ HUD Metro FMR Area	38.02%	15.17%	-6.33%
Charlotte-Gastonia-Rock Hill, NC-SC HUD Metro FMR Area	64.90%	1.40%	-10.80%
Fort Lauderdale-Pompano Beach-Deerfield Beach, FL Metro Division	68.22%	5.05%	-21.66%
Gary, IN HUD Metro FMR Area	71.69%	3.03%	-17.57%
Hartford-West Hartford-East Hartford, CT HUD Metro FMR Area	56.73%	0.39%	-0.05%
Jackson, MS HUD Metro FMR Area	79.97%	0.70%	-32.84%
Jacksonville, FL HUD Metro FMR Area	62.01%	2.86%	-16.71%
Monmouth-Ocean, NJ HUD Metro FMR Area	40.25%	-7.93%	4.41%
North Port-Bradenton-Sarasota, FL MSA	48.84%	9.15%	-14.83%
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD MSA	54.11%	10.19%	-26.97%
Sacramento–Arden-Arcade–Roseville, CA HUD Metro FMR Area	62.73%	7.67%	-9.62%
San Antonio-New Braunfels, TX HUD Metro FMR Area	68.61%	-4.63%	1.44%
Washington-Arlington-Alexandria, DC-VA-MD HUD Metro FMR Area	24.11%	3.63%	-14.96%
West Palm Beach-Boca Raton-Delray Beach, FL Metro Division	68.10%	3.00%	-9.25%

Notes: The table displays share of existing voucher holders in above 20% poverty census tracts in each SAFMRs mandatory metropolitan area in 2017. The excess concentration of African-American and White headed existing voucher holders are calculated by share of African-American and White headed households in above 20% poverty census tracts minus the share of all existing voucher holders in this metropolitan area that in above 20% poverty census tracts.