# The Effect of Targeted Subsidies on Poverty Exposure of Housing Voucher Recipients: Evidence from the Small-Area Fair Market Rents*

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**Abstract**

Prior research underscores the advantages for disadvantaged families relocated to affluent areas, but many using housing vouchers remain in poverty-stricken zones. Addressing this, in 2018, the U.S. Department of Housing and Urban Development (HUD) launched the Small-Area Fair Market Rents (SAFMRs) policy. This replaced metro-wide rent ceilings with ZIP-code-specific ones for Housing Choice Voucher beneficiaries across 24 metro areas, incentivizing relocation to better locales. Using extensive HUD data, our study examines the SAFMR policy's impact on housing decisions, landlords, and neighborhoods. With a dual empirical strategy, we analyze near-comparable metros and the real-world policy execution. Our findings show that SAFMR notably reduces poverty rates among recipients, driven by revamped housing options and shifts in landlord-tenant relations. This trend appears to be primarily driven by the initial placement of new voucher recipients, indicating that the moving costs for existing voucher holders present a substantial obstacle to the policy's effectiveness. Unlike earlier city-centric studies, ours offers a wider perspective, spotlighting the varying effectiveness across Metropolitan Statistical Areas (MSAs) and detailing 'voltage effects' of the policy's broader rollout.

Keywords: Housing Voucher, Affordability, Rent Ceiling, Small Area Fair Market Rent, Fair Market Rent

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# 1 Introduction

The Housing Choice Voucher (HCV) Program, the largest rental assistance initiative in the United States, plays a crucial role in supporting low-income households. As the nation's largest rental assistance program, the HCV Program aids more than 5 million individuals across 2.2 million low-income households, with 70% of voucher recipients belonging to families with children. Despite its substantial budget allocation, a comprehensive understanding of its broader impact and effectiveness remains elusive.

Particularly, a significant shortcoming of the program is its inability to fulfill its intended purpose of enhancing neighborhood choice for low-income recipients (Pollakowski et al. (2018), Ellen, O'Regan, and Harwood (2023)). Voucher holders frequently reside in neighborhoods with higher poverty rates, contradicting the program's aim of providing improved housing opportunities. This concentration of poverty can have profound implications, particularly for the well-being of children growing up in these communities (Chetty, Hendren, and Katz (2016)).

One source of concentrated poverty among voucher recipients is the program's reliance on a single subsidy ceiling, based on 'Fair Market Rent (FMR),' for an entire metropolitan area. The Metropolitan Statistical Areas' (MSAs) FMR is determined annually by the U.S. Department of Housing and Urban Development (HUD), typically equating to 40% of the asking rents in the recipient's metropolitan area, adjusted for bedroom size. In an effort to address this issue, HUD implemented the Small Area Fair Market Rents (SAFMRs) initiative in the Dallas metro area in 2011 as a pilot program. Unlike traditional FMR, SAFMRs set FMR at the ZIP code level, thereby adjusting the payment standards accordingly. This mandate significantly increased the generosity of the voucher subsidy in higher-rent neighborhoods in an effort to address concerns about racial segregation and expand the availability of housing in lower-poverty neighborhoods for voucher recipients (Collinson and Ganong, 2018). In 2018, the SAFMRs were expanded to include 24 MSAs. However, there is little empirical evidence documenting the impact of this broader roll-out.

This project examine the nationwide impact of changes in the housing voucher program's payment structure, focusing on the program expansion in 2018. By utilizing administrative data, which encompasses a comprehensive dataset of HCV recipients' location choices and their detailed characteristics from HUD, we aim to analyze the effects of this policy shift on the decisions made by voucher holders and associated stakeholders, namely non-voucher holders and landlords. We will draw upon in-depth institutional knowledge to ascertain the causal effects resulting from the program's implementation.

Specifically, two empirical strategies are used to causally identify effects. The first compares a treated group of voucher recipients in the metropolitan areas with HUD-mandated SAFMRs with a comparison group of recipients in similar metros that narrowly missed published inclusion criteria. As our alternative empirical strategy, we exploit within-metro variation. Within mandated metros, often several public housing authorities (PHAs) administer the voucher program and they varied significantly in their actual compliance in applying the mandate. The second empirical strategy leverages the differences in implementation within a metropolitan area to identify results.

In an extensive analysis of the Housing Choice Voucher Program, key findings emerged regarding its impact on voucher holders' exposure to poverty. Notably, there was a significant decrease in the average poverty exposure among voucher holders, with reductions ranging from 1.5% to 2%. This decrease is particularly noteworthy considering that only about 10-11% of the voucher holders actually relocated. The effects are even more pronounced for new entrants to the program. The most considerable benefits were observed among voucher holders who initially chose neighborhoods with poverty rates below 10%, experiencing an increase in their benefits of 22% to 25%. Overall, the policy effectiveness appears to be primarily driven by the initial placement of new voucher recipients, indicating that the moving costs for existing voucher holders present a substantial obstacle to the policy's effectiveness.

Diving deeper into the mechanisms, we find a noticeable increase in the family contributions of voucher holders in areas marked by lower rents. Furthermore, there was a surge in the number of entries in higher-rent zones, although there wasn't a statistically significant exits in the lower rent districts. When casting a glance at neighborhood spillover effects, preliminary observations indicate a decline in rents in the lower-rent zip codes, contrasted by an upswing in the higher-rent zip codes.

Lastly, the study revealed considerable heterogeneity across different MSAs. The effects of the program varied widely across metro areas and respective housing authorities. Given the metro-specific policy estimates, we conducted a regression to examine the correlations between the metro-specific variables and policy effectiveness across the 15 SAFMR-mandated MSAs. Utilizing the estimated coefficients, we eventually aim to forecast the potential policy effects in areas that have not yet adopted the small area payment standard.

This paper contributes to the existing literature on housing voucher programs by examining the underexplored impact of the new SAFMR payment scheme on various stakeholders. Previous studies have focused on the locational choices of low-income households receiving housing assistance and the interactions between landlords and policy measures. While the list isn't exhaustive, our research builds upon works such as Eriksen and Ross (2013), Eriksen and Ross (2015), Collinson and Ganong (2018), McMillen and Singh (2020), and Aliprantis, Martin, and Phillips (2022) highlight the complex interplay between landlords and policy measures, revealing their profound impact on the housing landscape. However, they have not fully addressed how changes in payment schemes like SAFMR affect the involved parties, an area this paper aims to illuminate.

Furthermore, the paper extends the scope of research from city-centric studies to a broader, nationwide context. Much of the prior work, like that in Washington D.C. (Aliprantis, Martin, and Phillips, 2022) and Dallas (Collinson and Ganong, 2018), is limited to urban areas. This study explores the 'voltage effects' (List, 2022) of housing policies when applied on a larger scale. As List (2022), Al-Ubaydli, Lai, and List (2023) suggest, for a policy to be successful, it must work effectively when scaled up. By investigating the nationwide implementation of changes in the housing voucher program's payment scheme, this paper adds a crucial dimension to the field. It moves from a city-centric view to a broader examination across multiple MSAs, highlighting the diverse regional effects of SAFMR policies and their real-world implications.

Section 2 provides the institutional setting. Section 3 outlines the data sources that we utilize. Section 4 details our across-metro variation strategy and within-metro variations. Section 5.1 shows the results of first-time recipients and Section 5.2 reveals the existing voucher holders' results. Section 6 investigates the landlord's reactions and neighborhood spillover effects, and Section 7 discusses MSA-level heterogeneity, respectively. Finally, Section 8 concludes.

# 2 Institutional Setting

## 2.1 Housing Voucher Program

The HCV program is a decedent of the Section 8 housing voucher program that enables recipients to contribute 30% of their gross household income as rent with the government subsidizing the gap between that contribution and the locally determined fair market rent (FMR). The local FMR is determined annually by the HUD, which is usually set equal to 40% of asking rents in the recipient's metropolitan area adjusted for bedroom size.

The initial aim behind implementing the HCV program was to assist low-income families in accessing communities that provide improved educational institutions and increased prospects for economic progress.

prior research has illustrated that voucher recipients experience less crowding, risk of homelessness, and recipient choice in where to live (Mills et al., 2006; Ellen, 2020). However, studies indicate that vouchers have been moderately effective in fulfilling this objective.

Figure 2 demonstrates the disproportionate clustering of voucher holders in neighborhoods with higher poverty rates compared to all renter households in the 50 largest cities in the United States. The x-axis represents the percentage of all renters residing in census tracts with a poverty rate exceeding 20% in each metropolitan area, as per the American Community Survey. The y-axis in the figure indicates the difference, in percentage points (pp), between the number of Housing Choice Voucher (HCV) recipients living in high-poverty areas and the overall percentage of renters in each metropolitan area. This disparity has been referred to as "excess concentration" by Eriksen and Yang (2022) and other researchers. Among the 50 largest metropolitan areas, Fresno (CA) had the highest percentage of renters living in high-poverty tracts, at 72.3%, while Nassau-Suffolk (NY) had the lowest, with only 9.9% of renters. The population-weighted average for all renters living in neighborhoods with poverty rates exceeding 20% in these 50 cities was 39.7%. In contrast, the population-weighted average for HCV recipients living in high-poverty tracts was 57.0%, resulting in an average excess concentration of 17.3%. Moreover, metropolitan areas with a greater proportion of renters residing in census tracts with higher poverty rates are more likely to experience this excess concentration phenomenon.

The HCV program's effectiveness in promoting housing mobility and providing recipients with genuine housing choices is being questioned in light of these findings. It calls for a closer examination of the factors contributing to the concentration of voucher holders in high-poverty neighborhoods, including the availability of affordable housing options in low-poverty areas and potential barriers, such as financial constraints, that prevent voucher holders from accessing them. This underscores the need for policy interventions and program improvements to address these disparities and promote fair housing opportunities for HCV recipients.

## 2.2 Early SAFMR Initiative

In 2011, HUD implemented the Small Area Fair Market Rents (SAFMRs) initiative in the Dallas metro area. This initiative was introduced in response to a lawsuit that alleged racial segregation resulting from a single metropolitan-wide payment standard.[1] The SAFMRs adjusted the payment standards at the ZIP code level, allowing for higher payments to landlords in neighborhoods with higher rents, while voucher

[1] See *Texas Department of Housing and Community Affairs et al., v. Inclusive Communities Project, Inc., et al.*

holders still contributed 30% of their income towards rent. In 2012, HUD expanded the ZIP code level payment standards to a demonstration program involving five public housing authorities in Chattanooga, TN, Chicago, IL, Laredo, TX, Long Beach, CA, and Mamaroneck, NY.

Research on the impact of the early stage of the SAFMR initiative has been relatively limited but significant. Collinson and Ganong (2018) provided the first evidence of SAFMR 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. Another study by focused on the landlord's reaction to SAFMRs in DC. The findings indicated minimal changes in landlords' background check processes and a relatively small-scale response to the new policy. Additionally, Dastrup, Finkel, and Ellen (2019) evaluated the effects of SAFMR implementation in the five demonstration housing authorities. 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.

## 2.3 Expansion of SAFMR

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 2017. Second, public housing authorities in 24 mandated Metropolitan Statistical Areas (MSAs) were required to adopt SAFMRs for determining rent ceilings for all HCV recipients starting in 2018. The primary statistical results of policy adoption are various by metropolitan areas, where housing assistant payment from local housing authorities are dramatically increased in mandatory areas while family contribution decrease substantially. These mandated MSAs were selected based on specific criteria[2].

- Number of Voucher Holders: At least 2,500 vouchers were in use in the metro area

[2]The criteria for selecting the mandated Metropolitan Statistical Areas (MSAs) for the SAFMRs were initially proposed by HUD. The first three criteria were proposed by HUD, and an additional criterion, as well as the requirement for the voucher concentration ratio's numerator, were added by HUD for the final rule based on public comments. The final rule also included the requirement for the numerator of the third criterion, which states that the percentage of voucher families living in concentrated low-income areas relative to all renters within the area must be at least 25 percent. However, since almost all voucher holders in metropolitan areas are concentrated in high-poverty areas compared to renters, we only consider the 155 percent threshold for our analysis.

- 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;

- 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 in the 24 MSAs starting no later than April 1, 2018. However, each PHA within the mandated areas had autonomy in choosing the actual adoption dates and was not required to use 100% SAFMRs as the subsidy payment standards. Some MSAs and PHAs meeting the criteria were excluded from the treated group in our empirical analysis for various reasons. This includes five HUD MSAs with a lack of observations[3] in our sample and those that had already adopted SAFMRs prior to April 2018[4]. Additionally, several PHAs (e.g., Atlanta Housing (GA), Philadelphia Housing Authority (PA), Housing Authority of the City of Pittsburgh (PA)) participates in the Move-To-Work program and hence the HUD gives them full discretion to modify the SAFMRs based on their local market condition. Most of these PHAs still follows the same rule for SAFMRs, but one housing authority opted out of the original SAFMRs setting, hence we exclude the Pittsburgh, PA HUD Metro FMR Area[5]) from our mandatory sample. Overall, we have 15 mandatory metros included in our empirical analysis.

Table 1 provides information on the 15 MSAs that meet the aforementioned criteria and were selected as the mandated MSAs by HUD. The first three criteria are directly downloaded from HUD's Initial Proposed Selection Tool. The Voucher Concentration is a census track-level measure that represents the ratio of

[3]This includes 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

[4]This includes Chicago-Joliet-Naperville, IL HUD Metro FMR Area, Dallas-Plano-Irving, TX Metro Division, and Fort Worth-Arlington, TX HUD Metro FMR Area. In addition, two PHAs, the City of Long Beach Housing Authority and the Town of Mamaroneck Housing Authority are also excluded due to the same reason.

[5]The City of Pittsburgh's 90 different neighborhood has very unique topography and some of them are less than a single square mile. Due to this fact and also the FMRs and SAFMRs are lower than the actually rent in the city, the Housing Authority of the City of Pittsburgh (PA) group several ZIP Code areas together, and use the average SAFMRs of those ZIP Codes as the "high payment standard" areas. Hence, the City of Pittsburgh only has one payment standards for the high rent areas. Thus, we also exclude Pittsburgh, PA HUD Metro FMR Area in the mandatory metros group. See Housing Authority of the City of Pittsburgh 2019 Moving to Work Annual Plan for details.

vouchers in a concentrated low-income area (CLIA) to the total number of vouchers, divided by the number of renter units in the CLIA to the total number of renter units. Concentrated low-income areas (CLIAs) are defined based on poverty rates and income thresholds. The Unit Concentration is a measure at the Zip Code Tabulation Area (ZCTA) level, calculated as the number of units in ZCTAs with SAFMRs above 110% of the metropolitan FMR divided by the total number of renter units in that ZCTA. The Rental Units Vacancy Rate is a metro-level measure that represents the number of vacant units for rent divided by the sum of the number of vacant units for rent, the number of renter-occupied units, and the number of rented but not occupied units. The American Community Survey's 5-year estimates for 2013 to 2017 were used to determine the metropolitan-level rental units vacancy rate.

# 3 Data

Our administrative data are acquired from the United States Department of Housing and Urban Development. The data contains households level records of those who participated in the housing choice voucher program. The household-level records contain household and family member identifiers, demographics, income, and geographic variables. Our data starts from 2005 to 2021, where we only use the data between 2012 to 2020 as our sample period to have a relatively short pre-treatment time and consistent Census designation, and more importantly, to rule out the potential impact of the COVID-19 pandemic in 2021. The data is an annual snapshot taken in December of every year, and thus we could only observe the status of the household in December of each year.

To generate variables associated with household status (e.g., if moved from another tract, if first-time recipients), we expand our sample to one year before the beginning year (2011) and one year after the ending year of the sample period (2021) when we clean the data. Our sample contains 2.85 million unique Section 8 Vouchers and Move-to-Work Tenant-based Vouchers from 2011 to 2021, which are composed of 17.8 million household-year records. We dropped 27,423 duplicated household-year observations in the MTW database if the household-year appeared both in Section 8 and MTW database since MTW data records contain a significant amount of missing value compared with Section 8 records. Additional 27 household-year observations are dropped due to purely duplication. For any household with any years missing, the households are also excluded (1.57 million households). A more detailed explanation of how we construct such a sample is described in Appendix A.

# 4 Identification Strategy

Our identification strategy relies on two aspects of the real policy adoption. The first is using the exogenous cutoffs when HUD selects the mandatory metro areas that require SAFMRs adoption. The second is using the policy execution variation at the Public Housing Authorities (PHAs) level.

## 4.1 Across Metro Area Variation

In our first empirical strategy, we compare the outcome of SAFMR-mandated MSAs with a comparison MSAs. We select our comparison group by relaxing each of the thresholds of criteria. The main reasoning behind such a strategy is that the non-mandated MSAs close to each threshold could have followed a similar trajectory with the mandated MSAs, as they are similar regarding the criteria mentioned above.

Table 2 presents how the comparison metros are selected. Our selection procedures are based on the four standards when HUD picked the mandatory metros. We only relax one standard each time and keep the other three constants. Our relaxation is based on the distributions of each standard of all metros in the HUD decision-making file. The detailed selection procedure is described in Appendix 3. 11 metros are selected into the comparison group using this method. In addition, four marginal metros met all four standards but are not included in the final 15 mandatory metros list in Table 1. Thus these four metro areas are also included in the comparison group. In total, we have 15 comparison metros for our empirical analysis, compared with 15 mandatory metros in the sample.

Figure 4 illustrates the actual adoption rate of PHAs in each metropolitan area included in our groups of 15 mandatory metros and 15 comparison metros of first-time recipients. PHAs in the mandated metros (colored in blue) began adopting the SAFMR policy in January 2018, and a significant increase in adoption is evident from June 2018. By January 2020, almost all PHAs in the mandated MSAs have adopted SAFMR. In contrast, the PHAs in the comparison metros (colored in red) do not adopt SAFMR throughout our sample periods, which generates variation for identification purposes.

Our empirical specification is based on the following two-way fixed effects regression. For household $i$ living in county $c$ in year $t$, the model is specified as follows:

$$\mathrm{Y}_{ict} = \alpha + \beta \mathrm{Mandatory}_c \times \mathrm{Post}_t + \lambda \mathbf{X}'_{it} + \delta_c + \zeta_t + \epsilon_{ict}$$

The model under consideration includes the dependent variables represented by $Y_{ict}$, such as the poverty rates of the household's census tract in 2010 or whether the household resides in a census tract with a poverty rate below certain thresholds (e.g., 20% or 10%). The variable $\text{Mandatory}_c$ takes a value of one if voucher holders are located in the mandatory Metropolitan Statistical Areas for Small Area Fair Market Rent, and $\text{Post}_t$ equals one if the date of voucher holders is after March 31st, 2018.[6] $\mathbf{X}_{it}$ refers to a set of household head-level control variables, such as race, gender, and age of household head, if have any children or disabled members, and the number of household members. The model incorporates county fixed effects, $\delta_c$, and calendar year-fixed effects, $\zeta_t$, to account for time-invariant county-level unobserved factors and overall macro time trends, respectively. The standard errors are clustered at the metro level to address the unobserved annual correlations within the metro areas.

It is noteworthy that not all PHAs in the mandated Metropolitan Statistical Areas (MSAs) adopted Small Area Fair Market Rents (SAFMR), despite the fact that the mandated PHAs were more likely to adopt them than PHAs in non-mandated MSAs. Leveraging these institutional observations, our main empirical specifications focus on the Intention-to-Treat (ITT) analyses. In the ITT approach, the mandatory designation of SAFMRs is used directly as the treatment, represented by the variable $Mandatory_c \times Post_t$. The identifying assumption for ITT is that the random assignment of treatment (i.e., SAFMR mandatory designation) is independent of potential outcomes, which means that, in expectation, the only systematic difference between the treatment and comparison groups is the treatment assignment itself. This assumption allows for unbiased estimation of the causal effect of the treatment, even if some PHAs in the treatment group do not actually receive the treatment (i.e., non-compliance) or some individuals in the control group do receive the treatment (i.e., contamination).

To empirically test whether there exist different pre-existing trends in our outcome variables between the treated and comparison groups, we plot an event study graph in Figure A1. Specifically, the event study graph plots the $\beta_t$ coefficients for all $t \in \{2012, \ldots, 2020\}$ from the following regression:

$$\text{Y}_{ict} = \alpha + \sum_{t=2012}^{2020} \beta_t \times \text{Mandatory}_c \times \text{Post}_t + \delta_c + \zeta_t + \epsilon_{ict}$$

where the subscripts denote household $i$ at year $t$ living in county $c$. The dependent variable is the

[6] To construct this date variable, we use calendar year as the year variable and the month-day from the effective date as the month-day variable to determine the post-treatment sample, due to sample's data entry issue that effective date may not get updated timely. The effective date is the contract renew/start date for the voucher recipients (Collinson and Ganong, 2018)

surrounding voucher holder's tract poverty rate, $\delta_c$ denotes the county fixed effects, and $\zeta_t$ denotes the calendar year fixed effects. Mandatory is equal to one if voucher holders are in the mandatory metros. Post is equal to one if the effective date of voucher holders after March 31st, 2018, indicates that their effective Fair Market Rent is equal to the Small Area Fair Market Rent if treated. Standard errors are clustered at the household level. Before the SAFMR is mandated in the treated MSAs, we do not observe any particular trends between treated and comparison groups, which validates our empirical strategy and selection of comparison groups. Starting from 2017, when the mandated MSAs began adopting SAFMR, the census tract poverty level of the voucher holders in the treated groups started to decline relative to the comparison groups. In the next section, we investigate these results in more detail.

## 4.2 Within Metro Area Variations

In this section, we explore how we leverage variations at PHA-level within SAFMR-mandated Metropolitan Statistical Areas (MSAs). We exploit a unique institutional setup to identify these variations. While HUD mandated the use of SAFMRs by PHAs in the 24 MSAs starting in April 2018, each PHA within the SAFMR-mandated MSAs had the discretion to adopt the new policy either earlier or later (Refer to Figure 4 for first-time voucher recipients, and Figure 5 for existing voucher holders). Additionally, households have to wait on a waiting list before entering the program, and the exact duration to find a suitable unit is highly uncertain. Consequently, voucher recipients cannot time the market or deliberately choose to start their contract after the associated PHA implements the SAFMR standard, to maximize the benefits of the higher payment standard induced by SAFMRs, making SAFMR adoption at the household level seemingly random. Within this institutional context, we investigate how the outcomes of households using SAFMR as a payment standard differ from those households unable to use SAFMR[7]. Unlike the across-MSAs identification strategy, this within-Metro specification does not rely on the selection of control MSAs.

However, there exists an endogeneity issue in regressing our outcome variables of interest (e.g., the poverty rate of the neighborhoods where the household locates) and indicator variables whether or not the households' voucher payment standard is based on SAFMR. For instance, suppose that households with

[7] To illustrate this further, consider the following extreme example. A household that received a voucher from a non-SAFMR-mandated housing authority, unaware of SAFMRs, decides to carry the voucher and move to one of the mandatory areas. Voucher holders already located in the mandatory areas have a competitive advantage in choosing or relocating to lower-poverty areas with higher rents because their payment standards are based on specific zip codes. On the other hand, households that moved with the non-SAFMR-mandated vouchers may still use the metro-wide payment standard as their benchmark when receiving the subsidy. Consequently, landlords in high-rent areas are more likely to approve applications from households that can leverage a higher amount of subsidy.

better socioeconomic characteristics are more likely to be aware of the SAFMR policy and actively seek to utilize it to secure housing in more desirable neighborhoods with lower poverty rates. These households may have more resources to navigate the voucher system effectively and have access to information about the benefits of using SAFMR as their payment standard. In this scenario, the decision to use SAFMR as the payment standard is related to the household's choices, which are also related to the outcome variable, the poverty rate of the neighborhood where the household resides.

To address this endogeneity concern, we use the 'peer's' adoption rate of the SAFMR initiative at the PHA level as an instrumental variable. Given that the policy mandate was imposed in April 2018, majority of the PHAs started adopted around this date and some may adopt as late as 2019. Specifically, here's how our first-stage regression is set up for household $i$ residing in PHA $p$, counties $c$, in year $t$.

$$\mathbb{I}(\text{EFMR=SAFMR})_{i,p,c,t} = \alpha + \gamma \text{Adoption Rate}_{-i,p,c,t} + \lambda \mathbf{X}'_{i,t} + \delta_c + \zeta_t + \epsilon_{i,p,c,t}$$

where the dependent variable (i.e., endogenous variable) equals one if households use SAFMRs as their effective Fair Market Rent (EFMR), denoted as $\mathbb{I}(\text{EFMR=SAFMR})_{i,p,c,t})$. The instrumental variable (i.e., Adoption Rate$-i, p, c, t$) indicates the SAFMR adoption rate of peers who are in the same PHA, which is calculated as follows:

$$\text{Adoption Rate}_{-i,p,c,t} = \frac{\text{N}_{-i,p,c,t}\{(i) : \text{EFMR}_i = \text{SAFMR}_i, i \in \text{Time-Metro-PHA}_{p,c,t})\}}{\text{N}_{-i,p,c,t}\{(i) : i \in \text{Time-Metro-PHA}_{p,c,t})\}}$$

where, the ratio represents the number of observations (excluding household $i$) located in county $c$, receiving a housing voucher from PHA $p$, and using SAFMR as their EFMR at time $t$, divided by the total number of observations (excluding household $i$) located in county $c$, receiving a housing voucher from PHA $p$ in year $t$. Note that if the denominator is zero, we replace this ratio with 0 since most situations involve voucher holders carrying vouchers from PHAs that are not located in the current metro. For first-time recipients, we modify the adoption rate and use the lag one month level without excluding one household.

For household $i$ residing in metro $c$ at time $t$, the second-stage regression is as follows:

$$\text{Y}_{i,c,t} = \alpha + \beta \widehat{\mathbb{I}(\text{EFMR=SAFMR})}_{i,t} + \lambda \mathbf{X}'_{i,t} + \delta_c + \zeta_t + \epsilon_{i,c,t}$$

In this equation, $Y_{ict}$ represents the variables of interest (e.g., poverty rate), $\widehat{\mathbb{I}(\text{EFMR=SAFMR})}_{it}$ denotes the predicted values from the first stage, $\mathbf{X}'_{it}$, $\delta_c$, $\zeta_t$ represent household-level control variables, county, and year-month fixed effects, respectively.

The identifying assumptions for our instrumental variable strategy are as follows: First, the PHA-level adoption rate of SAFMR is a good predictor for a household's likelihood of using SAFMR as their payment standard, given that the policy is adopted at the PHA level. Second, the monotonicity assumption holds, as the PHA-level adoptions should influence the SAFMR adoption decision for households in a consistent direction. The higher the PHA-metro level adoption rate is, the higher the probability of the households use SAFMRs as their payment standard will be. Furthermore, since voucher holders cannot time the market and choose the contract start date (month) to benefit from the zip-wide payment standard due to the highly uncertain waiting time and unit availability within 90 days, the instrument remains independent of any unobservable factors.

# 5 Results

In this section, we present the primary results using the identification strategies described previously. Our primary outcome variables are the poverty rate of the census tract surrounding the households of the voucher recipients and a binary variable indicating whether the household resides in a tract with a poverty rate below a specified threshold. We divide our samples into two groups: first-time recipients[8] who have just entered the program (Section 5.1) and existing voucher holders who have continued in the program (Section 5.2). Robustness checks are presented in Section 5.3.

## 5.1 First-Time New Voucher Recipients

**Across Metro Area Identification Results** In this section, we examine first-time housing voucher recipients, focusing on those receiving vouchers for the first time. Table 4 presents our main regression findings, utilizing variations across MSAs, comparing SAFMR mandated MSAs and comparison MSAs. In Panel A, where we use the poverty rate as the key variable for our sample of first-time recipients, Columns (1) and (2) show results based on the tract-level poverty rate from the 2010 Census for these voucher recipients. Our findings indicate that, on average, the SAFMR policy leads to first-time voucher holders in treated MSAs residing in neighborhoods with a poverty rate reduction of 0.97 to 0.99 percentage points. This decrease

[8]Our first-time recipients are defined as households appearing in the dataset for the first time. We do not have the first placement record for any households accepted before the start of our investigation in 2012.

represents a significant 3.7% reduction in poverty, considering the average poverty rate is between 26.3% and 26.9%. Notably, for voucher holders initially choosing neighborhoods with poverty rates under 20% in mandatory metro areas post-April 2018, we observe an increase in benefits ranging from 10.8% to 10.9%, as indicated in Columns (3) and (4). The most substantial benefits, detailed in Columns (5) and (6), are seen among voucher holders who initially select neighborhoods with poverty rates below 10%, experiencing increases of 22% to 25%.

**Within Metro Area Identification Results** It is important to note that these are intent-to-treat (ITT) estimates, which require cautious interpretation. In our ITT analysis, we evaluate the effects based on the mandatory status of MSAs at the aggregate level, regardless of whether individual voucher holders were directly impacted by the SAFMR payment standards or if there were deviations from the policy's protocol. Additionally, this analysis pools effects across all voucher holders, without distinguishing the specific number who relocated following the implementation of the SAFMR initiative.

Table 5 highlights outcomes stemming from an analysis concentrating on within-metro variations, as articulated in Section 4. This empirical approach address the issue of actual adoption of SAFMRs by each PHA, which generates Treat-on-Treat (ToT) estimates of the program effectiveness. In Column (2) and Column (4), outlines results without and with household-specific control variables, adopting the instrumental variable (IV) strategy. OLS estimations in Column (1) and Column (3), juxtaposed against the IV outcomes in Column (2) and Column (4), manifest a marginal upward bias in the OLS projections. Such bias emerges from endogeneity complications, wherein households procuring more generous voucher subsidies might opt for locales with diminished poverty rates, forging a correlation between the subsidy and the residual in the OLS regression. Consequently, OLS outcomes amplify the genuine causal effect of augmented voucher subsidies on the poverty rates of chosen locales. In contrast, IV outcomes in Column (2) and Column (4) utilize exogenous instrumental variables, effectively addressing this endogeneity bias. Banking on the assumption that households can't synchronize their voucher receipt dates and hence can't react deliberately opt for SAFMR as the payment standard, the IV strategy furnishes a more precise estimation of the genuine causal effect. The IV findings hint at a marginally robust link between receiving augmented voucher subsidies and settling in localities with diminished poverty rates.

In a nutshell, the SAFMR payment criterion, by proffering elevated subsidies in higher-rent zones, has tangibly motivated voucher holders to select neighborhoods characterized by diminished poverty rates and elevated rents. Crucially, outcomes using within-metro variations resonate in magnitude and consistency with findings in Table 4, rooted in "across-metro" variations, even sans the deployment of comparison metros as control groups. This corroborates the precision of our policy impact estimations across both identification methodologies. This intimates that the SAFMR policy has exerted a notable influence on the residential preferences of voucher holders, culminating in a significant decrease in the poverty rates of their chosen neighborhoods.

**Household Contribution, Subsidy, and Rent** In Panel B of Table 4, we present regression outcomes focusing on the attributes of voucher recipients, specifically examining how their contribution and subsidy amounts are influenced by the policy changes. This analysis is stratified by neighborhoods based on the ratio of SAFMR to Metro level Fair Market Rent. The objective here is to assess the impact of policy innovations on the financial contributions of voucher recipients and to partially evaluate the policy's effectiveness.

Columns (1) and (2) reveal an increase in household contributions as a percentage of income for first-time recipients in areas with lower rent, while no significant change is observed in regions with higher rent. These findings align with the policy's intent to augment subsidies in higher-income areas, while gradually reducing them in areas with lower rent. However, despite this intended policy direction, we do not notice a change in the subsidy amount (as a proportion of the voucher holders' monthly adjusted income) in Columns (3) and (4). In areas with higher rent, there is a noticeable increase in gross rent (which we've standardized by dividing it by the corresponding Fair Market Rent), but this trend is not evident in lower-rent areas.

## 5.2 Existing Voucher Holders

In this section, we explore the impact of the SAFMR on the location choices of existing voucher holders. For our analysis, existing voucher holders are defined as those in the full sample, excluding first-time placements. These households may either choose to remain in their current locations post-policy adoption or may no longer qualify as voucher holders for various reasons. Addressing these confounding factors is crucial for a clear analysis.

Table 6 and Table 7 show the regression results when examining the effects of the SAFMR policy on existing voucher holders using poverty rate and household attributes as dependent variables. The constant term in Columns (1) and (2) of Table 6 show that the average tract-level poverty rate for this group is approximately 25-26.5 percentage points. The compulsory implementation of SAFMR has a treatment effect of -0.31 – -0.33 percentage points, which translates to a 1.24% reduction in the poverty level experienced by voucher recipients. This outcome remains consistent even after adjusting for household-level control variables, such as gender, age, race, and ethnicity of the household head, presence of children in the household, and total household size. Columns (3) and (4) use a binary variable to identify households in census tracts with poverty rates below 20%. SAFMR's mandatory adoption increases the proportion of households in these lower-poverty tracts by 2.5% to 2.6%, both with and without household-level control variables. Columns (5) and (6) introduce a binary variable for households in tracts with poverty rates below 10%, where the most significant effects are observed. Implementing zip code-level payment standards in 15 metro areas, as opposed to metro-wide standards, raises the proportion of households in tracts with poverty rates below 10% by 2.8% to 3.2%.

Figure 5 illustrates the adoption rate of public housing authorities in each metro area for existing voucher holders, defined by the leave-one-out current month number of adopters divided by the total number of voucher holders renewing their contracts. Correspondingly, Table 8 presents regression results using within-metro variation for existing voucher holders. These results show a pattern similar to that of first-time recipients, albeit with a smaller magnitude.

Testing the move behavior of existing voucher holders offers an explanation for the observed estimates. Table 9 presents the probability of these holders moving. The data shows that existing voucher holders in mandatory metro areas are less likely to relocate compared to those in comparison metro areas, as indicated in Columns (1) and (2) of the table. However, among those who do move, there is a higher likelihood of relocating to areas with lower poverty rates compared to their previous addresses, as demonstrated in Columns (3) and (4). There is no significant difference in the likelihood of moving to areas with higher or the same poverty rates, conditioned on the change of address. These findings highlight how the moving behavior of existing voucher holders contributes to changes in the overall distribution of poverty rates across areas.

## 5.3 Robustness Checks

In this section, we conduct robustness checks to validate the empirical specifications and data constructions. Specifically, we address specific identification concerns for across-MSA. A series of robustness checks overall validates our regression results.

**Sensitivity Analysis** Our cross-MSA identifications rely on the selection of control groups described in Section 4. Our selection procedures using several benchmarks are detailed in Appendix 3. A major concern regarding our selection breakpoints is that these cutoffs are not randomly chosen. Therefore, we conducted a sensitivity analysis by varying the level of relaxation for one of the four HUD benchmarks, as shown in Figure A2. By keeping the other three cutoffs consistent and relaxing only one of them to a lower level each time, the results in Figure A2 indicate that our main estimates remain relatively stable below zero. The only benchmark that's somewhat less stable when relaxed is the Unit Concentration; while the results remain negative, they sometimes become statistically insignificant. Overall, regression coefficients tend to stay stable when we adjust the thresholds.

**Alternative Control Group** Our comparison metros in our core results are selected by relaxing benchmark, while another concern is raised due to the baseline is highly selected. Thus we also compare our main specification with all remaining records and also the top 100 largest metros (by number of voucher holders) in Table A1. Column (3) and (4) in Table A1 shows the results using all records as the control group without and with the households level control variables, and Column (5) and (6) shows the results using the top 100 most voucher recipients households occupied HUD defined MSA. Not suprisingly, using a larger sample attenuates the final estimates but does not change dramatically. There is still a 1 percent poverty rate reduction. Overall, there is no significant variation when using alternative control groups for poverty reduction in mandatory metros.

**Alternative Post-Treatment Indicator** Our main specification utilizes a combined measure for post-treatment status, as our data is captured as a snapshot every December. This unique measure combines the calendar year and the month-day of households' effective date of their payment standard, whether SAFMR or FMR. By doing so, we can precisely identify the specific date when the new payment standard became effective or when the payment standards changed from metro-wide to zip-wide due to the contract renew. However, some may argue that using only the calendar year would be a sufficient indicator for the post-treatment period. This is because the contract date (modified date in the data) indicates that some PHAs started using SAFMR as early as the first month of 2018. To address this concern, we conduct a robustness check, using the calendar year as the post-indicator instead of using post-March 31st, 2018 as the indicator. Panel A of Table A2 presents the results using the full sample, while Panel B of Table A2 displays the results using the new voucher recipients sample. Overall, the effects and magnitudes obtained from this robustness check are consistent with our main specification.

# 6 Landlord Reaction and Spillover Effects

In this section, we delve deeper into the mechanisms driving the policy effectiveness we've identified in earlier results. Recall that in the institutional setting outlined in Section 2, we observed an increase in the payment standard, particularly in areas with higher rents (i.e., higher SAFMR). Building on this, we now turn our attention to landlords' behaviors in response to such shifts. We specifically analyze how they adjust rents charged to voucher holders pre- and post-implementation of the SAFMR initiatives across various neighborhoods. Furthermore, we investigate their choices concerning property entry and exit within the market.

## 6.1 Unit Entry and Exit

Next, we delve into how landlords respond to adjusted monetary incentives by examining entries, exits, and the total number of units receiving vouchers in mandated Metropolitan Statistical Areas (MSAs). The willingness of landlords to accept these vouchers plays a critical role in determining the number of voucher holders who can access higher-quality neighborhoods. Fortunately, our administrative data provides precise addresses of the voucher holders' residences, allowing us to define annual entry and exit decisions for each rental unit.

Table 10 presents the impact of the SAFMR mandate status on entries, and exits of units. A unit's entry in year $t$ is defined as one occupied by a voucher holder in our data in year $t$ but not appeared before. On the other hand, a unit's exit refers to one occupied until year $t-1$ but no longer occupied by a voucher recipient in year $t$. In Panel A of Table 10, we examine how the SAFMR mandate status affects the total number of units, as well as the number of entries and exits at the unit level. Overall, the total number of entries in SAFMR-mandated MSAs experienced a notable increase of 3.99 percent (Column (1)) compared to control MSAs. As anticipated, this increase was more significant in census tracts with a poverty rate of less than 20% (Column (2)) compared to tracts with higher poverty rates (Column (3)). We observed a 5.22 percent increase in newly entered units in low-poverty areas (tracts with less than a 20% poverty rate, Column (2)). However, there were no distinct increases in entry in higher-poverty areas (Column (3)). No significant effects on exit decisions were detected in either low or high-poverty areas (Column (5), Column (6)). This is consistent with the contract rents results that there is no significant rent decrease in lower poverty areas, 'De facto', even though the defined payment standard in these areas is lowered 'De jure'.

The overall findings confirm that the increased subsidies in higher-rent and lower-poverty areas, resulting from the SAFMR mandate, have strengthened landlords' incentive to accept voucher holders. This boost in landlord outreach has enabled voucher holders to expand their choices of rental units, as supported by (Ellen, 2020). Consequently, it motivates these voucher holders to seek better-quality neighborhoods, thus validating the program's effectiveness.

## 6.2 Spillover Effects on Non-Voucher Holders' Rent

In the previous sections, we have demonstrated that the adoption of SAFMR serves to guide voucher holders towards lower-poverty neighborhoods, underscoring the effect of the SAFMR initiative on voucher recipients and landlords. But what repercussions does this have for the surrounding community? We investigate whether there are any spillover effects on the rents of non-voucher holders (Eriksen and Ross, 2015). For this exploration, we harness the "Real Page Rent Index[9]", a profound resource detailing rental patterns in the multifamily property sector across major U.S. cities. This index provides property-specific data such as the precise address, relevant property traits, the year of construction, the aggregate number of units, their average dimensions, occupancy rates, along with the average proposed and actual rent values. The richness of this dataset facilitates the assessment of rents on a per-square-foot basis, marking it as the dependent variable, all while accounting for diverse property attributes.

Figure 7 uses a simple AR model to forecast the rent of the metro areas in our sample and compare the forecast rent and the actual rent to show the spillover effects of the policy adoption. All results seem like no spillover effect from the policy because the number of voucher holders are relative small in each areas, one figure is noteworthy. In Panel (d) of Figure 7, the forecast error is the largest in area with more voucher holders, compared with comparison metros. This results sheds light on the potential existing of spillover effect of the SAFMR adoption in higher rent area with more demand side pressure.

[9]Source: https://www.realpage.com/analytics/

# 7 Metro-level Heterogeneity and Prediction on Policy Effectiveness

## 7.1 Heterogeneity by Metros

In this section, we delve into the MSA-level heterogeneity. The Department of Housing and Urban Development is actively exploring the expansion of the SAFMR policy. In light of this, understanding the diverse effects and nuances across different metropolitan areas becomes paramount. Each area has its unique socio-economic dynamics, housing markets, and demographic distributions. Such diversity can significantly affect the efficacy and implications of policies like SAFMR. By understanding these nuances, we gain insights into tailoring policies to specific contexts, ensuring optimal outcomes for beneficiaries and informing HUD's decisions on future policy implementations.

Figure 8 demonstrates the policy's effectiveness at the metro level. Each dot in the figure represents the effect of SAFMR on the average poverty exposure of voucher holders in each metro area, with a focus on the significant variations among the mandatory metro areas. This is indicated for first-time voucher holders (x-axis) and for existing voucher holders (y-axis). Negative estimates indicate a successful reduction in poverty due to SAFMR's impact in each metro.

There are a couple of key takeaways regarding metro-level heterogeneity. Firstly, there is significant variability in policy effectiveness across MSAs, with some (e.g., Fort Lauderdale (FL), North Port (FL), San Antonio (TX), Monmouth-Ocean (NJ), Washington DC, and Gary (IN)) showing markedly higher effectiveness than others (e.g., Jacksonville (FL), Jackson (MS), Sacramento (CA), Charlotte (NC)). Secondly, the policy's effectiveness varies more significantly for first-time voucher holders compared to existing voucher holders. These surprising findings need further investigation.

## 7.2 Prediction on Policy Effectiveness

Given the metro-specific policy estimates, we conducted a regression to examine the correlations between the metro-specific variables and policy effectiveness across the 15 SAFMR-mandated MSAs. Our dependent variable focuses on the effects of SAFMR on policy reductions in each of these 15 MSAs. For explanatory variables, we primarily utilize the policy determinant criteria that HUD employed when initially selecting the SAFMR mandatory metros. These criteria include the percentage of voucher units in SAFMR greater than

110% of FMR, the excess poverty concentration rate of voucher holders relative to that of overall renters, the move rate to lower poverty tracts, the percentage of recipients in tracts with below a 10% poverty rate, and the average SAFMR-to-FMR ratio at year 2017 (pre-adoption) to avoid any lookahead bias.

Panel A in Table 11 presents the regression results. Notably, Column (2) of Panel A, which displays the standardized effects, reveals that these variables are statistically significantly correlated with policy effectiveness. However, a deeper dive into the interpretation and directionality of these variables is needed.

Utilizing the estimated coefficients, we eventually aim to forecast the potential policy effects in areas that have not yet adopted the small area payment standard. Specifically, we predict the policy effectiveness for the 30 largest metros among those not yet adopting. Panel B of Table 11 lists the top 10 metro areas where the policy effects are forecasted to be most pronounced. For instance, in San Francisco and Minneapolis, SAFMR is projected to reduce the average poverty exposure of voucher holders by 1.5 percentage points. Nonetheless, more detailed analysis is required for precise predictions of policy effectiveness.

# 8 Conclusion

Mandated SAFMRs have resulted in a moderate shift in housing voucher recipients to lower-poverty areas in 15 metropolitan areas. These effects are highly non-linear and primarily the result of new recipients first receiving a voucher after the imposed mandate in April 2018. After the introduction and mandatory adoption in 15 metropolitan areas, there has been a slight shift in the distribution of housing choice voucher recipients to lower-poverty neighborhoods. This change is primarily attributable to the new recipients, who never had a voucher before but now have the option to use a higher subsidy amount to reside in a community with more opportunities. Our results also indicate a more educated housing authorities dramatically provides comparative advantages for existing housing voucher recipients to relocate towards to lower poverty areas. This implication compliment the "voltage effect" model developed by Al-Ubaydli, Lai, and List (2023), that reduce the information asymmetry could helps the SAFMRs program's efficacy at a consistent level once the program expands to a larger scale.

Despite the fact that the targeted subsidy for housing choice voucher holders reduces exposure to poverty, other effects remain unknown and are beyond the scope of this paper. Nonetheless, poverty exposure mitigation is an adequate response to the majority of questions, and voucher holders surrounding tract poverty rates are less concentrated, indicating that they are more dispersed and evenly distributed and less concentrated in high poverty areas. Voucher recipients are more likely to live in areas with a high poverty rate because the rent is lower, it is simpler to obtain an apartment, or they have social connections (Ellen, 2020). The following research question concerns the characteristics and location of voucher-holder households before and after being observed by the program. Modeling and uncovering the trajectory of voucher recipient households and how the targeted subsidy mitigates poverty exposure in unobserved locations when households no longer receive the subsidy requires additional research.

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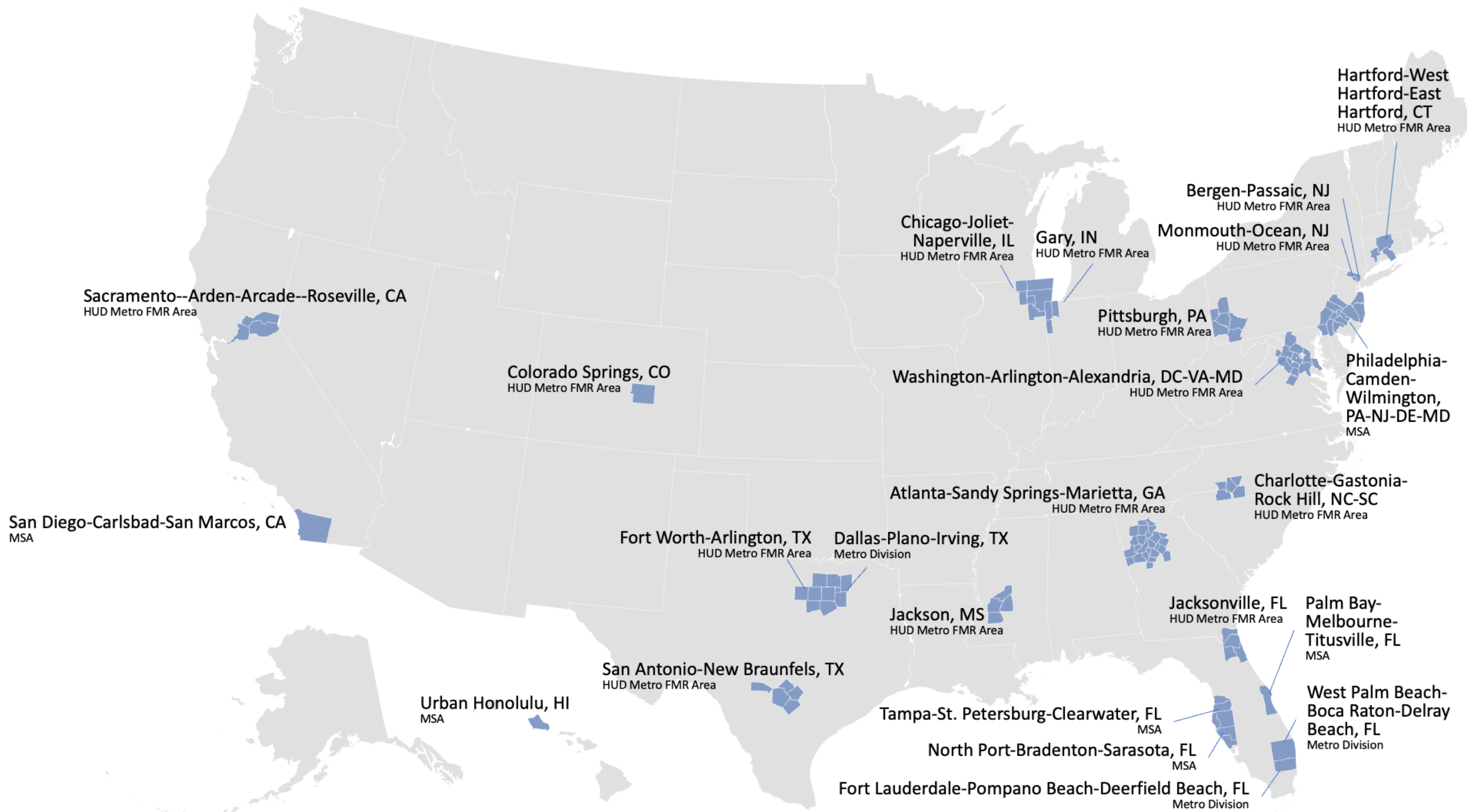
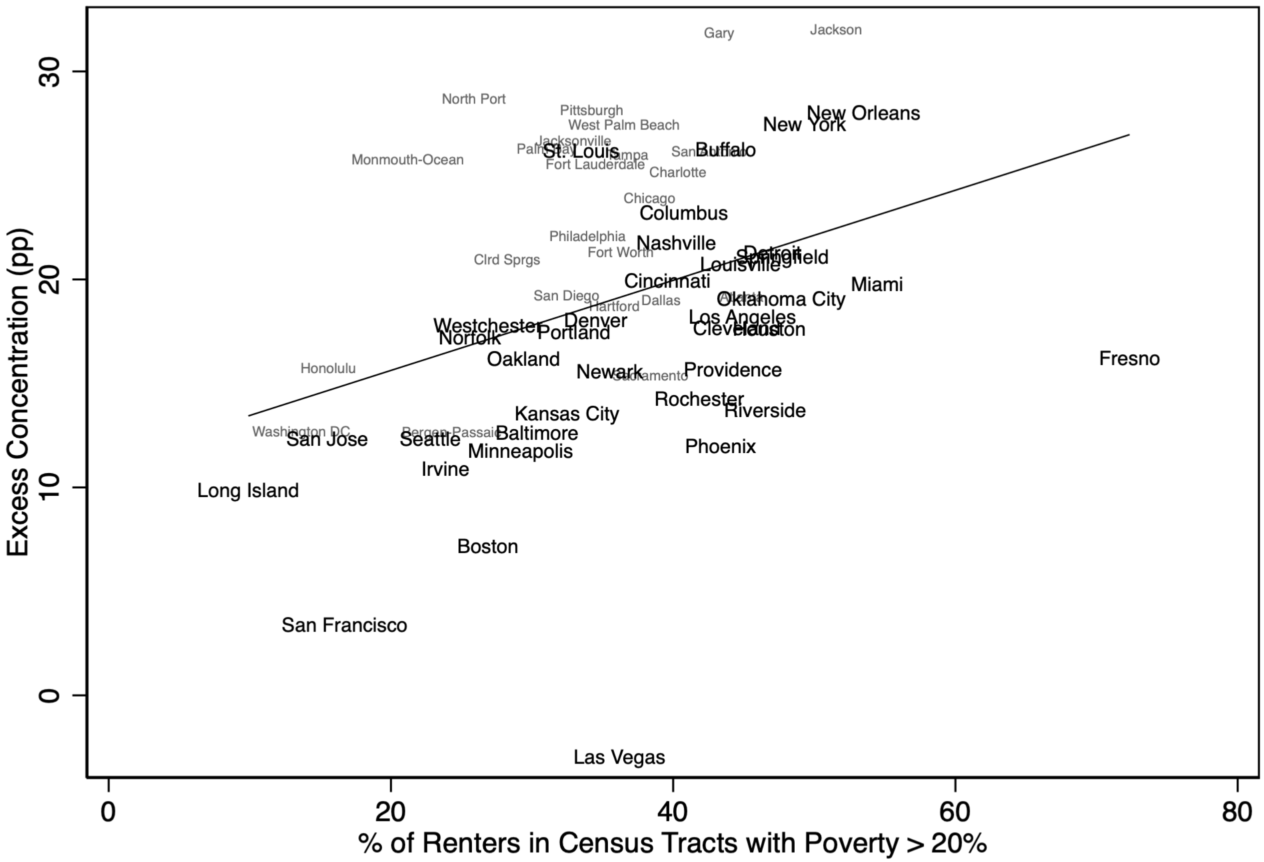
**Figure 1: 24 Mandatory Adoption Metros**




*Notes:* The map displays the 24 required metro (HUD defined) areas that must employ a zip-wide payment standard starting in April 2018 for public housing authority. The geographic definitions of the metro areas can be accessed from the HUD website. Five metro areas are missing from our administrative data's observations, including 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.

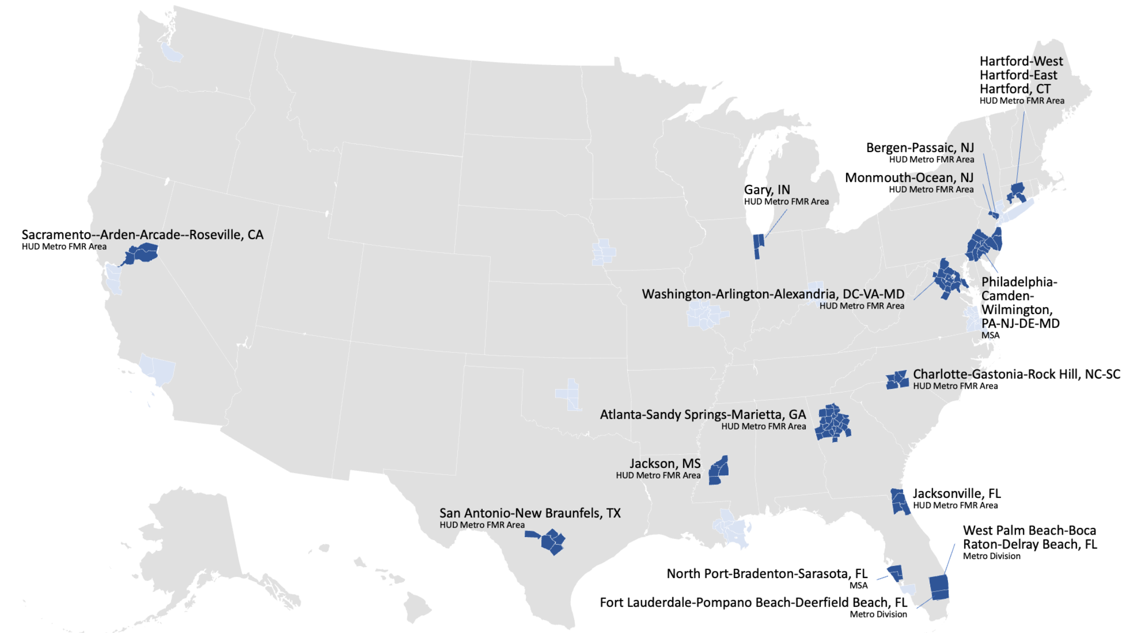
**Figure 2: Excess Concentration of Voucher Holders in Major Metropolitan Areas**



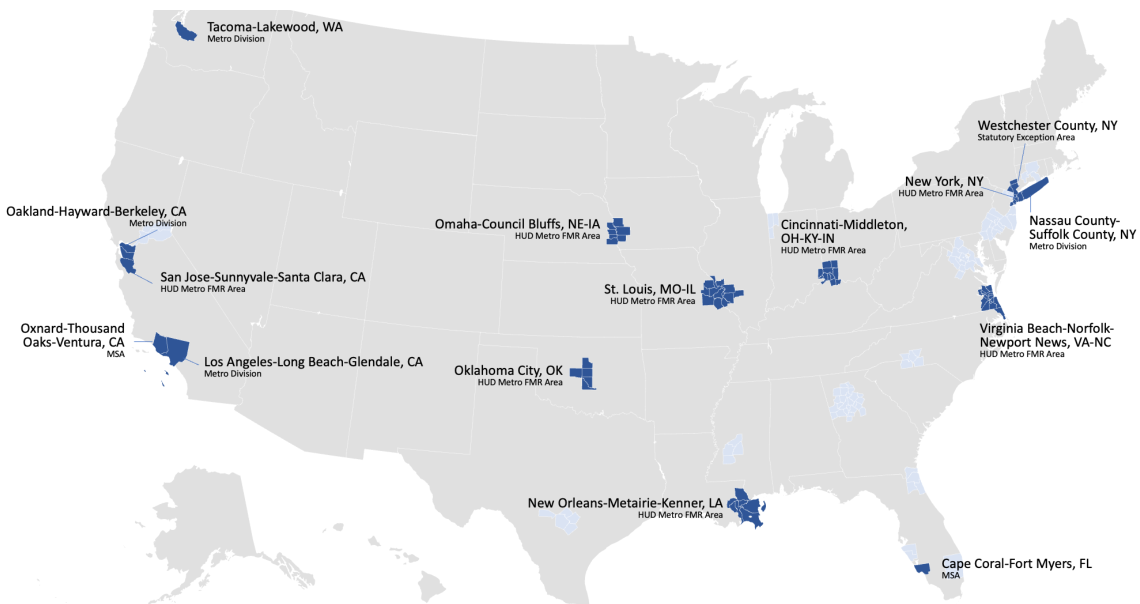

*Notes:* The map displays the excess concentration rate of the average percentage points of voucher holders in census tract with poverty rate above 20% with respect to the average share of renters in such tracts, for the 50 largest HUD Fair Market Rent metro areas based on the total number of voucher recipients in 2016.

## Figure 3: Mandatory Metros and Comparison Metros in the Sample

(a) 15 Mandatory Metros

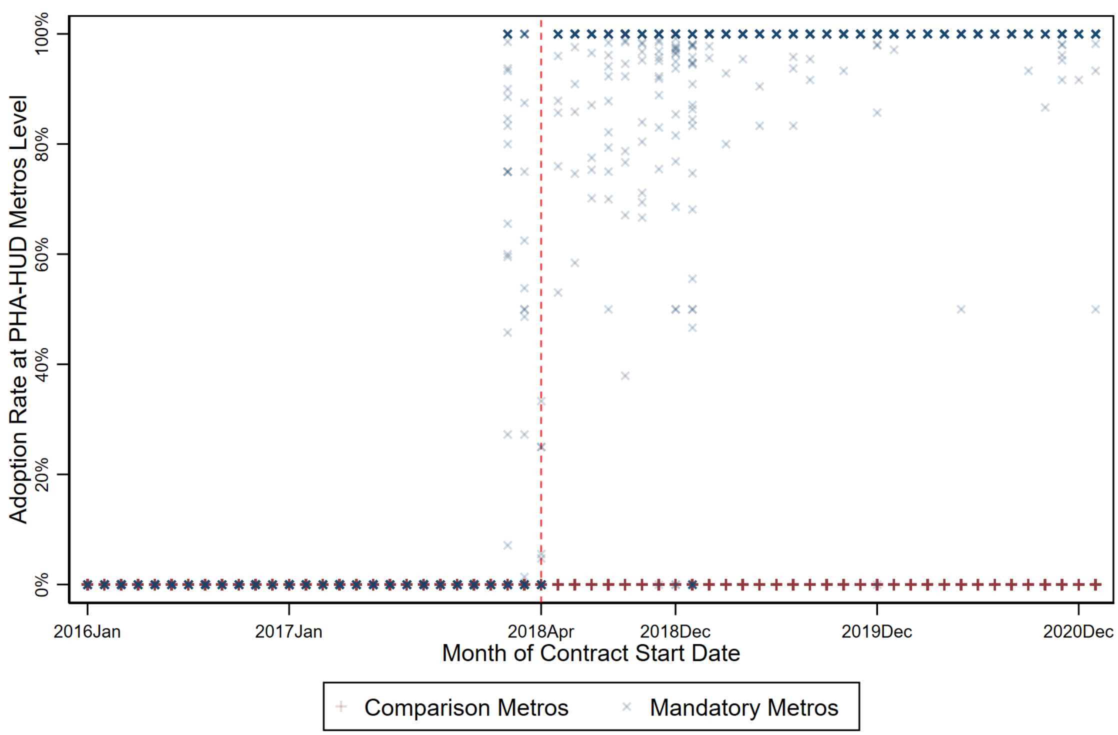



(b) 15 Comparison Metros



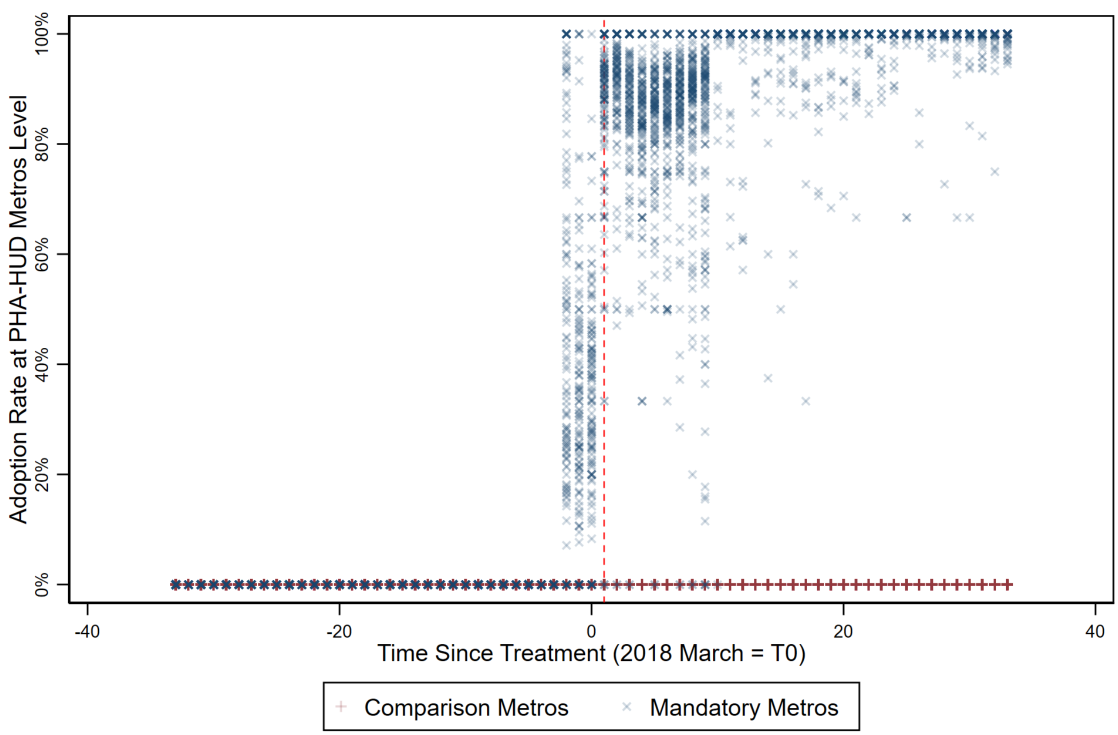

*Notes:* Panel (a) displays the 15 mandatory metros in our mandatory group sample. Certain mandatory metros lack household voucher observations are excluded. Neither pre-treated nor untreated metros are included in this sample. Panel (b) displays the 15 comparison metros in our sample group for comparison. The comparison metros were chosen by relaxing the criteria and including metros that met the criteria but was not in the final list.

**Figure 4: Small Area Fair Market Rent Adoption Rate of First-Time Voucher Recipients by Time Since Treatment**



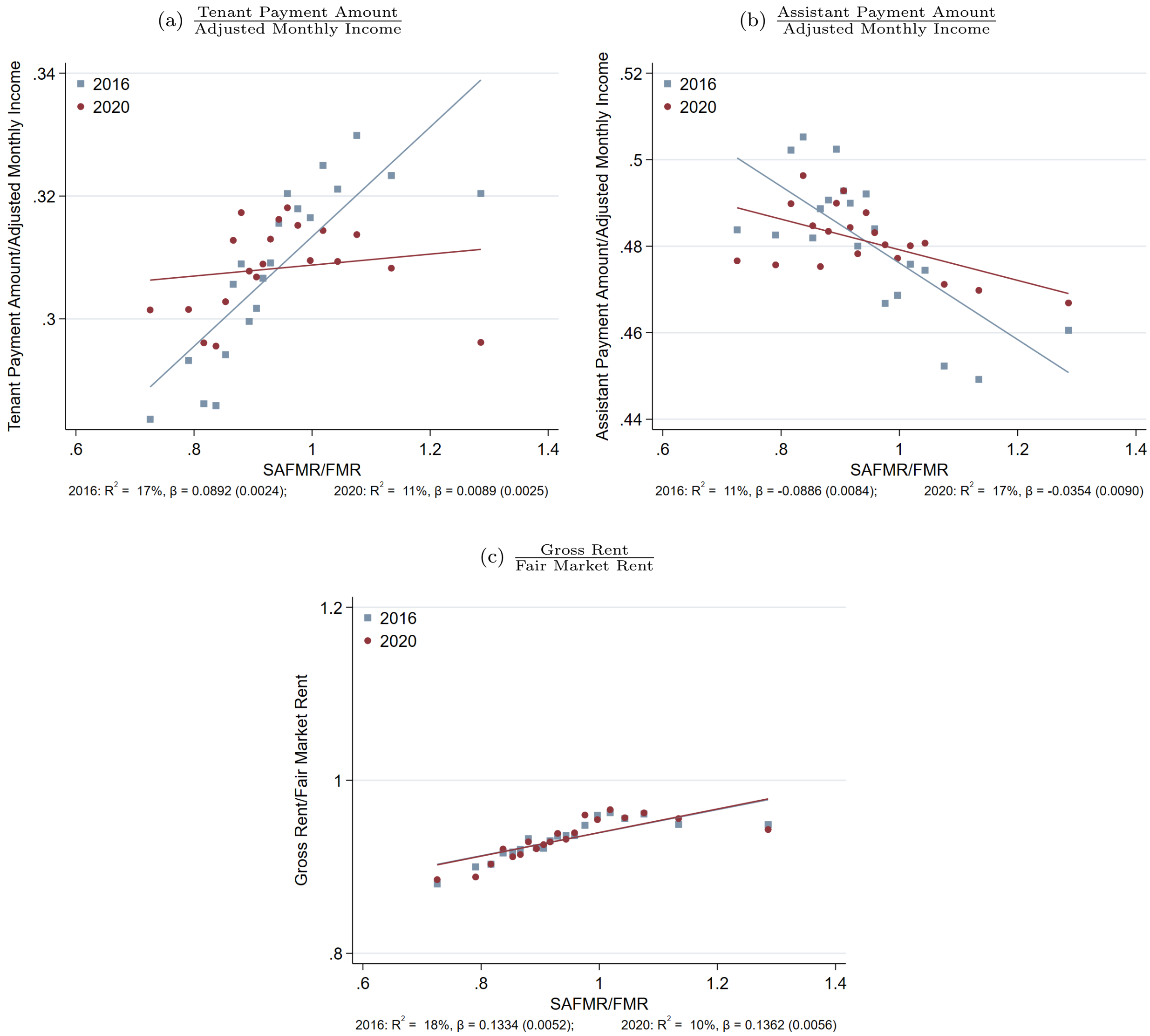

*Notes:* The figures illustrate the actual adoption rate of public housing authorities (PHAs) in each metropolitan area included in our groups of 15 mandatory metros and 15 comparison metros, based on the month and year of the effective date of the household level record. Mandatory metros are colored in blue and comparison metros are colored in red.

**Figure 5: Small Area Fair Market Rent Adoption Rate of Existing Voucher Recipients by Time Since Treatment**



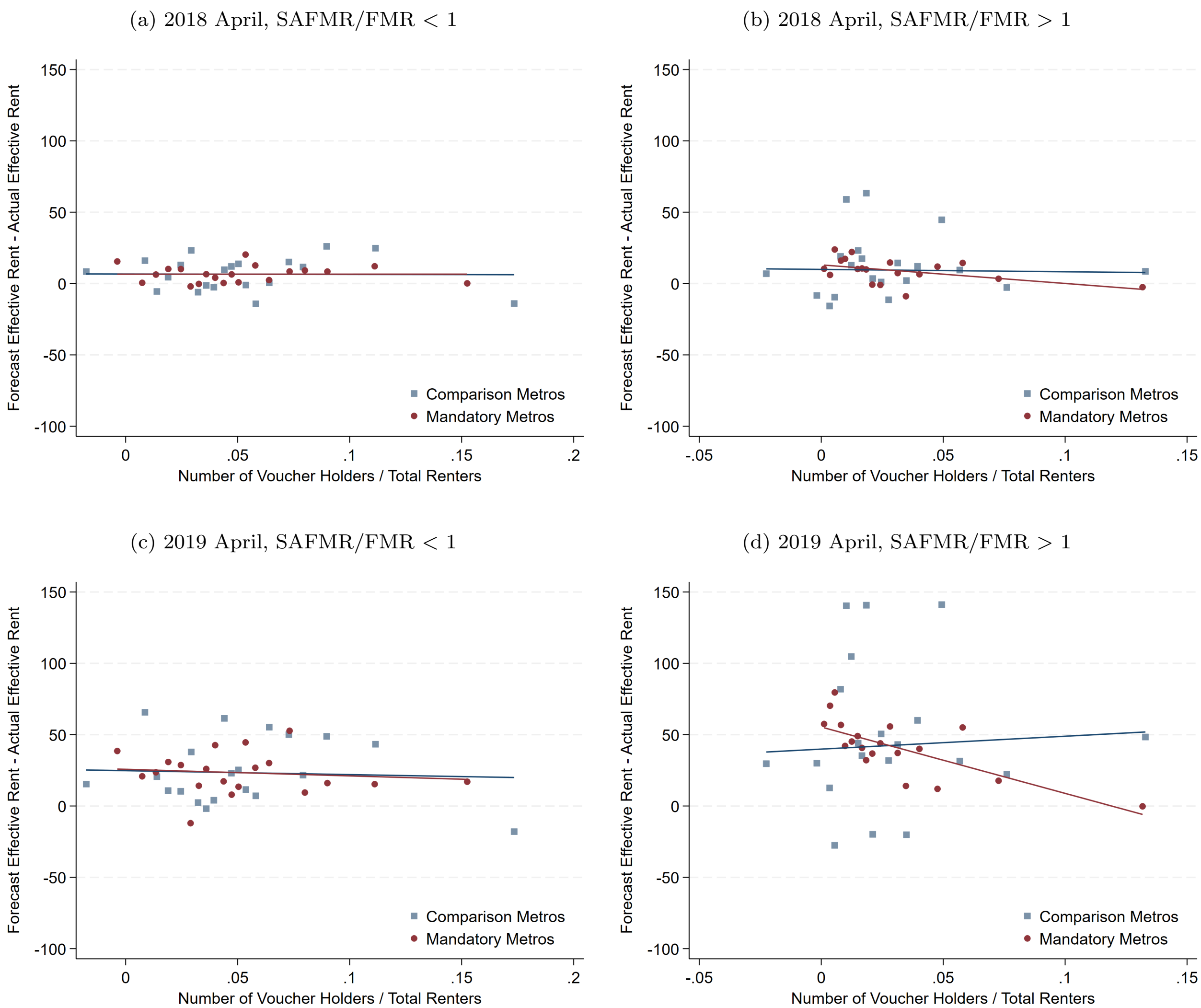

*Notes:* The figures illustrate the actual adoption rate of public housing authorities (PHAs) in each metropolitan area included in our groups of 15 mandatory metros and 15 comparison metros, based on the month and year of the effective date of the household level record. Mandatory metros are colored in blue and comparison metros are colored in red.

**Figure 6: Attributes of Existing Voucher Holders and Neighborhood Quality**



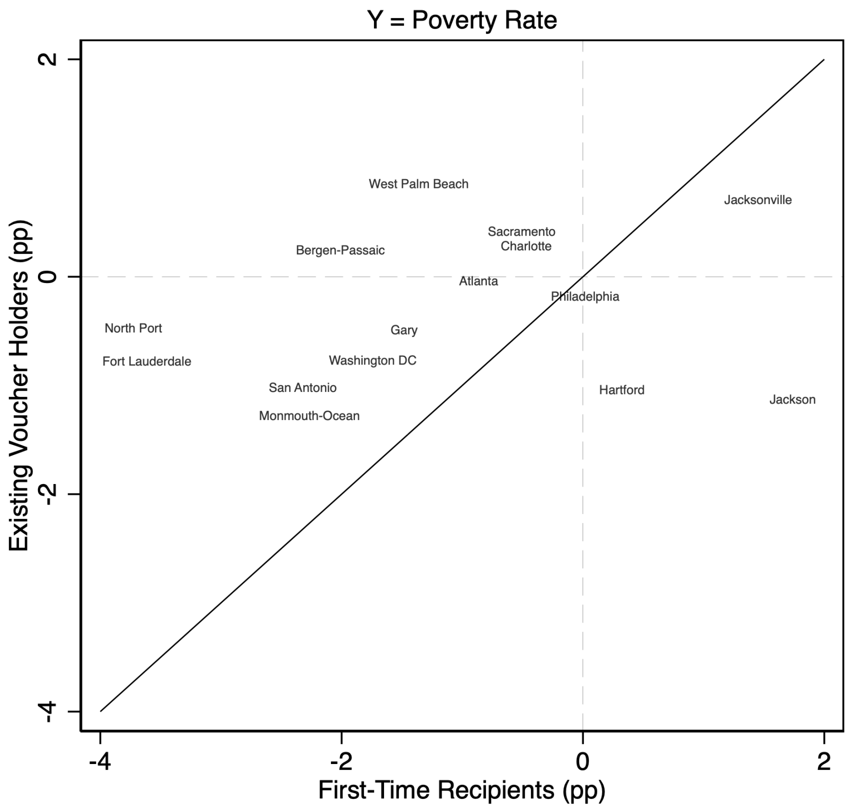

*Notes:* The plot utilizes restricted data from 2016 and 2020, focusing solely on voucher recipient households that relocated and currently reside in the 15 mandatory metros. In Panel (a), we regressed the household-level tenant payment amount, sourced from the household, against the household-level SAFMR to FMR ratio. In Panel (b), we regressed the assistant payment amount, from the local housing authority, against the household-level SAFMR to FMR ratio. Panel (c) uses the household level gross rent to fair market rent ratio. The housing assistance payment amount and the housing assistance payment amount are adjusted to 2016 dollars. Each dot on the plot represents the mean value for one of the 20 quantiles of the ZIP code-level SAFMR/FMR distribution, conditional on the PHA-HUD metro-year for both 2016 and 2020.

**Figure 7: Externalities: Forecast vs. Actual Effective Rents by SAFMR/FMR Ratio and Voucher Holder Concentration**




*Notes:* The figures are plotted by regress the property level difference between forecaste and actual effective rent against the voucher holder concentrations, defined by the number of voucher holders in 2016 at ZIP Code level divided by total number of renters in that ZIP Code. Each dot represent the median value of 20 quintile, controlling for number of units and average unit size of each property and also metro fixed effect. The forecast rent is defined by a simple model, that includes the monthly fixed effects, time fixed effects, and time since treatment fixed effects. Standard errors are adjusted by Newey-West estimator for heteroskedastic and autocorrelated of the error term.

**Figure 8: Heterogeneity Regression Results by Mandatory Metros**




*Notes:* The figure presents the regression results using each mandatory metro every time and compared with all comparison metros. The y-axis denotes the existing voucher holder sample results and the x-axis denotes the first-time recipients results. The dependent variable is voucher holders' surrounding census tract poverty rate. Additional households level attributes are controlled.

**Table 1: Mandatory Metros**

| | 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 presents how the mandatory metros are selected. HUD's selection benchmarks are downloaded from HUD's website, merged in rental units vacancy rate from Social Explorer 5-Year ACS (2013-2009). 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 FMR area with a poverty rate of 25 percent or more, or any tract in the metropolitan FMR 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). Unit Concentration (Zip Code Tabulation Areas level measure) is defined as number of units in ZCTAs with SAFMR above 110% Metro FMR divided by the number of all renter units in that ZCTA. 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. Besides, five HUD metros are excluded due to 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; Tampa-St. Petersburg-Clearwater, FL MSA). Three metros (Chicago-Joliet-Naperville, IL HUD Metro FMR Area; Dallas-Plano-Irving, TX Metro Division; Fort Worth-Arlington, TX HUD Metro FMR Area) and two Public Housing Authorities (PHAs) (City of Long Beach Housing Authority and Town of Mamaroneck Housing Authority) are excluded due to treat before 2018 April. Pittsburgh, PA HUD Metro FMR Area is also excluded due to not adopt SAFMR at Zip Code level after 2018 April.

**Table 2: Comparison Metros**

| | 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. HUD's selection benchmarks are downloaded from HUD's website, merged in rental units vacancy rate from Social Explorer 5-Year ACS (2013-2009). 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 FMR area with a poverty rate of 25 percent or more, or any tract in the metropolitan FMR 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). Unit Concentration (Zip Code Tabulation Areas level measure) is defined as number of units in ZCTAs with SAFMR above 110% Metro FMR divided by the number of all renter units in that ZCTA. 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.

**Table 3: Summary Statistics of Voucher Recipients Sample**

Panel A: Voucher Recipients' Surrounding Census Tract Poverty Rate in 2010 Census

| | Mean | SD | P10 | P25 | P50 | P75 | P90 |
|---|---|---|---|---|---|---|---|
| *15 Mandatory Metros* | | | | | | | |
| 2016 | 23.30 | 13.48 | 6.78 | 12.22 | 21.64 | 32.59 | 42.21 |
| 2020 | 23.15 | 13.92 | 6.42 | 11.67 | 21.15 | 32.61 | 42.79 |
| *15 Comparison Metros* | | | | | | | |
| 2016 | 25.98 | 13.67 | 9.01 | 15.15 | 24.72 | 34.77 | 44.11 |
| 2020 | 26.48 | 14.00 | 9.07 | 15.37 | 25.29 | 35.47 | 45.15 |

Panel B: Voucher Recipients' Attributes by Surrounding Census Tract Poverty Rate

| *15 Mandatory Metros* | <10% | <20% | >20% | >30% | Overall |
|---|---|---|---|---|---|
| *2016* | | | | | |
| # of Obs | 40,727 | 95,846 | 114,145 | 64,453 | 209,991 |
| Shares | 0.1939 | 0.4564 | 0.5436 | 0.3069 | 23.2958 |
| *2020* | | | | | |
| # of Obs | 44,569 | 101,612 | 113,470 | 65,987 | 215,082 |
| Shares | 0.2072 | 0.4724 | 0.5276 | 0.3068 | 23.1528 |

*Notes:* Panel A reports the all voucher recipients surrounding tracts poverty rate based on 2010 census, by mandatory or comparison group in 2016 and 2020. Panel B reports the 15 mandatory metros voucher recipients attributes by voucher recipients surrounding tracts poverty rate.

**Table 4: SAFMR Effects: First-Time Voucher Recipients**

Panel A: Census Tract Poverty Rate Measurements as Dependent Variables

| Y = | Poverty Rate | | <20% Poverty | | <10% Poverty | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Mandatory × Post | -0.9717*** | -0.9936*** | 0.0418*** | 0.0417*** | 0.0339*** | 0.0336*** |
| | (0.3373) | (0.3368) | (0.0111) | (0.0108) | (0.0067) | (0.0068) |
| Constant | 26.2963*** | 26.8463*** | 0.3843*** | 0.3860*** | 0.1378*** | 0.1477*** |
| | (0.1030) | (0.4851) | (0.0035) | (0.0114) | (0.0021) | (0.0082) |
| FEs | Year-Month | Year-Month | Year-Month | Year-Month | Year-Month | Year-Month |
| | County | County | County | County | County | County |
| Control | | Households | | Households | | Households |
| $N$ | 284,370 | 284,370 | 284,370 | 284,370 | 284,370 | 284,370 |

Panel B: Voucher Recipients Attributes as Dependent Variables

| Y = | $\frac{\text{Tenant Payment Amount}}{\text{Monthly Adjust Income}}$ | | $\frac{\text{Assistant Payment Amount}}{\text{Monthly Adjust Income}}$ | | $\frac{\text{Gross Rent}}{\text{Fair Market Rent}}$ | |
|---|---|---|---|---|---|---|
| | (1) $\frac{\text{SAFMR}}{\text{FMR}} < 1$ | (2) $\frac{\text{SAFMR}}{\text{FMR}} \geq 1$ | (3) $\frac{\text{SAFMR}}{\text{FMR}} < 1$ | (4) $\frac{\text{SAFMR}}{\text{FMR}} \geq 1$ | (5) $\frac{\text{SAFMR}}{\text{FMR}} < 1$ | (6) $\frac{\text{SAFMR}}{\text{FMR}} \geq 1$ |
| Mandatory × Post | 0.0159*** | -0.0019 | -0.0103 | 0.0070 | -0.0007 | 0.0461*** |
| | (0.0026) | (0.0021) | (0.0076) | (0.0081) | (0.0115) | (0.0164) |
| Constant | 0.3150*** | 0.3211*** | 0.4010*** | 0.4083*** | 0.9809*** | 1.0216*** |
| | (0.0015) | (0.0019) | (0.0070) | (0.0093) | (0.0095) | (0.0121) |
| FEs | Year-Month | Year-Month | Year-Month | Year-Month | Year-Month | Year-Month |
| | County | County | County | County | County | County |
| Control | Households | Households | Households | Households | Households | Households |
| $N$ | 80,998 | 40,067 | 80,998 | 40,067 | 80,998 | 40,067 |

*Notes:* The sample is restricted to first-time voucher recipients. Panel (A) shows the results using the first-time voucher recipients' surrounding census tract poverty rate attributes and Panel (B) shows the results using household level attributes as the dependent variable. A set of household head-level control variables such as race, gender, number of children, age, and the number of households are included as control variables. Standard errors are clustered at HUD MSA-year and presented in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

**Table 5: Adoption Rate Variation: First-Time Voucher Recipients**

| | w/o Controls | | w/ Controls | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | OLS | IV | OLS | IV |
| SAFMR Determined HAP | -0.8685*** | -0.9488*** | -0.8991*** | -0.9826*** |
| | (0.2982) | (0.3276) | (0.2961) | (0.3259) |
| FEs | County | County | County | County |
| | Year-Month | Year-Month | Year-Month | Year-Month |
| Control | | | Households | Households |
| $1^{st}$ Stage: Adoption Rate | | 0.9685*** | | 0.9684*** |
| | | (0.0037) | | (0.0037) |
| $1^{st}$ Stage KP F-Stat | | 68,831 | | 68,869 |
| Mean Poverty Rate (2016) | 25.5138 | 25.5138 | 25.5138 | 25.5138 |
| $N$ | 278,864 | 278,864 | 278,864 | 278,864 |

*Notes:* The sample is restricted to first time voucher recipients. Columns (1) and (3) report the regression results using the OLS regression without and with the household level control variables. Columns (2) and (4) report the regression results using the IV regression without and with the household level control variables, where the exogenous variable is the PHA level adoption rate in each metro area. The regression specification is as follows:

$$\mathrm{Y}_{ict} = \alpha + \beta \mathbb{I}(\widehat{\text{EFMR=SAFMR}})_{it} + \lambda \mathbf{X}'_{it} + \delta_c + \zeta_t + \epsilon_{ict}$$
$$\mathbb{I}(\widehat{\text{EFMR=SAFMR}})_{it} = \alpha + \gamma \text{Adoption Rate}_{-i,t} + \lambda \mathbf{X}'_{it} + \delta_c + \zeta_t + \epsilon_{ict}$$

where the subscripts denote household $i$ at year $t$ live in county $c$. $\delta_c$ denotes the county fixed effects. $\zeta_t$ denotes the calendar year-contract month fixed effects. Adoption $\text{Rate}_{it}$ denotes the public housing authority level share of voucher holder's effective FMR equates to SAFMR in that specific metro the households living at. $\mathbf{X}_{it}$ indicates a set of household head-level control variables such as race, gender, number of children, age, and the number of households. Standard errors are clustered at HUD MSA-PHA-year-month and presented in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

**Table 6: SAFMR Effects on Poverty: Existing Voucher Holders**

| Y = | Poverty Rate | | <20% Poverty | | <10% Poverty | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Mandatory × Post | -0.3284*** | -0.3148*** | 0.0106*** | 0.0101*** | 0.0047** | 0.0042** |
| | (0.0843) | (0.0824) | (0.0025) | (0.0024) | (0.0019) | (0.0019) |
| Constant | 25.0692*** | 26.4940*** | 0.4021*** | 0.3922*** | 0.1482*** | 0.1488*** |
| | (0.0210) | (0.6338) | (0.0006) | (0.0131) | (0.0004) | (0.0059) |
| FEs | Year-Month | Year-Month | Year-Month | Year-Month | Year-Month | Year-Month |
| | County | County | County | County | County | County |
| Control | | Households | | Households | | Households |
| $N$ | 3,870,382 | 3,870,382 | 3,870,382 | 3,870,382 | 3,870,382 | 3,870,382 |

*Notes:* The sample is restricted to existing voucher holders. The table shows the results using existing voucher holders' surrounding census tract poverty rate attributes. A set of household head-level control variables such as race, gender, number of children, age, and the number of households are included as control variables. Standard errors are clustered at HUD MSA-year and presented in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

**Table 7: SAFMR Effects on Households: Existing Voucher Holders**

| Y = | $\frac{\text{Tenant Payment Amount}}{\text{Monthly Adjust Income}}$ | | $\frac{\text{Assistant Payment Amount}}{\text{Monthly Adjust Income}}$ | | $\frac{\text{Gross Rent}}{\text{Fair Market Rent}}$ | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| SAFMR Determined HAP | 0.0064*** | 0.0075*** | -0.0043 | -0.0206*** | 0.0250** | -0.0276*** |
| | (0.0019) | (0.0018) | (0.0046) | (0.0037) | (0.0110) | (0.0085) |
| Constant | 0.3076*** | 0.3175*** | 0.2583*** | 0.4636*** | 0.9996*** | 0.9306*** |
| | (0.0018) | (0.0004) | (0.0054) | (0.0014) | (0.0135) | (0.0049) |
| FEs | Year-Month | Year-Month | Year-Month | Year-Month | Year-Month | Year-Month |
| | County | Households | County | Households | County | Households |
| Control | Households | | Households | | Households | |
| $N$ | 1,432,454 | 1,377,218 | 1,432,454 | 1,377,218 | 1,432,453 | 1,377,218 |

*Notes:* The sample is restricted to existing voucher holders. The table shows the results using household level attributes as the dependent variable. A set of household head-level control variables such as race, gender, number of children, age, and the number of households are included as control variables. Standard errors are clustered at HUD MSA-year and presented in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

**Table 8: Adoption Rate Variation: Existing Voucher Holders**

| | w/o Controls | | w/ Controls | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | OLS | IV | OLS | IV |
| SAFMR Determined HAP | -0.3558** | -0.4085*** | -0.3507*** | -0.3966*** |
| | (0.1396) | (0.1527) | (0.1323) | (0.1447) |
| FEs | County | County | County | County |
| | Year-Month | Year-Month | Year-Month | Year-Month |
| Control | | | Households | Households |
| $1^{st}$ Stage: Adoption Rate | | 1.0000*** | | 1.0000*** |
| | | (0.0000) | | (0.0000) |
| $1^{st}$ Stage F-Stat | | 2,040,253,122 | | 1,888,302,736 |
| Mean Poverty Rate (2016) | 24.9932 | 24.9932 | 24.9932 | 24.9932 |
| $N$ | 3,869,335 | 3,869,335 | 3,869,335 | 3,869,335 |

*Notes:* The sample is restricted to existing voucher holders. Columns (1) and (3) report the regression results using the OLS regression without and with the household level control variables. Columns (2) and (4) report the regression results using the IV regression without and with the household level control variables, where the exogenous variable is the PHA level adoption rate in each metro area. The regression specification is as follows:

$$\mathrm{Y}_{ict} = \alpha + \beta \widehat{\mathbb{I}(\mathrm{EFMR{=}SAFMR})}_{it} + \lambda \mathbf{X}'_{it} + \delta_c + \zeta_t + \epsilon_{ict}$$
$$\widehat{\mathbb{I}(\mathrm{EFMR{=}SAFMR})}_{it} = \alpha + \gamma \text{Adoption Rate}_{-i,t} + \lambda \mathbf{X}'_{it} + \delta_c + \zeta_t + \epsilon_{ict}$$

where the subscripts denote household $i$ at year $t$ live in county $c$. $\delta_c$ denotes the county fixed effects. $\zeta_t$ denotes the calendar year-contract month fixed effects. Adoption Rate$_{it}$ denotes the public housing authority level share of voucher holder's effective FMR equates to SAFMR in that specific metro the households living at. $\mathbf{X}_{it}$ indicates a set of household head-level control variables such as race, gender, number of children, age, and the number of households. Standard errors are clustered at HUD MSA-PHA-year-month and presented in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

**Table 9: Existing Voucher Holders: Probability of Move**

| Y = | Move | | Move to Better | | Move to Worse | | Move to Same | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Mandatory × Post | -0.0110*** | -0.0109*** | 0.0197** | 0.0201** | -0.0041 | -0.0040 | -0.0156 | -0.0161 |
| | (0.0028) | (0.0028) | (0.0086) | (0.0085) | (0.0085) | (0.0084) | (0.0130) | (0.0129) |
| Constant | 0.0931*** | 0.1443*** | 0.4168*** | 0.4521*** | 0.3846*** | 0.3811*** | 0.1987*** | 0.1668*** |
| | (0.0008) | (0.0029) | (0.0027) | (0.0070) | (0.0026) | (0.0063) | (0.0043) | (0.0081) |
| FEs | Year-Month County | Year-Month County | Year-Month County | Year-Month County | Year-Month County | Year-Month County | Year-Month County | Year-Month County |
| Control | | Households | | Households | | Households | Households | Households |
| $N$ | 3,870,382 | 3,870,382 | 354,095 | 354,095 | 354,095 | 354,095 | 354,095 | 354,095 |

*Notes:* The table shows the results using the existing voucher holder sample. The Column (1) and (2) show the probability of move of existing voucher holders. The Column (3) to (8) shows the results of moving to lower poverty rate, to higher poverty rate tracts, and to the tracts with the same poverty rate, comparing to the pre-move poverty rate. Standard errors are clustered at X-level and presented in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

**Table 10: The Entry and Exit of Units Occupied by Housing Voucher Holders**

| Y = | log(N.Entry) | | | log(N.Exit) | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Sample | Overall | <20% Poverty | >20% Poverty | Overall | <20% Poverty | >20% Poverty |
| Mandatory × Post | 0.0399* | 0.0522** | 0.0265 | 0.0010 | 0.0176 | 0.0111 |
| | (0.0229) | (0.0240) | (0.0411) | (0.0193) | (0.0181) | (0.0370) |
| County FEs | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FEs | Yes | Yes | Yes | Yes | Yes | Yes |
| $N$ | 134,028 | 94,437 | 39,591 | 134,028 | 94,437 | 39,591 |

*Notes:* Panel A uses all voucher recipients sample in our mandatory and comparison groups. Columns (1), (2) and (3) report the regression results using only the net entered units, while columns (4), (5) and (6) report the results using only the exited units at the tract level. New entered units are defined as the units that appeared in our data that no previously occupied by any voucher holders, and exited units are defined as the units are no longer occupied by recipients. The regression specification is as follows:

$$\mathrm{Y}_{ict} = \alpha + \beta \mathrm{Mandatory}_c \times \mathrm{Post}_t + \lambda \mathbf{X}'_{it} + \delta_c + \zeta_t + \epsilon_{ict}$$

where the subscripts denote household $i$ at year $t$ live in county $c$. $\delta_c$ denotes the county fixed effects, $\zeta_t$ denotes the calendar year fixed effects. $\mathbf{X}_{it}$ indicates a set of household head-level control variables such as race, gender, number of children, age, and the number of households. Asian includes Asian and Pacific Islander, and Other Race includes Native Americans and other multi-race headers. Mandatory is equal to one if voucher holders are in the mandatory metros. Post is equal to one if the effective date of voucher holders after March 31st of 2018. Standard errors are clustered at HUD MSA-year and presented in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

**Table 11: Policy Effect and Prediction**

**Panel A: Standardized Effects of the Policy Effects**

| Variables | (1) | (2) |
|---|---|---|
| | Coefficients | Standardized Effects ((1)/SD) |
| Percent all units in SAFMR > 110% FMR | 5.784* | 1.9409 |
| Excess concentration of voucher recipients | -.0829* | -2.1673 |
| Move rate of lower poverty tract | -22.4953* | -1.8418 |
| Percent recipients in below 10% poverty tract | -7.5393*** | -3.3872 |
| Average SAFMR/FMR ratio | -9.4393** | -2.4162 |

**Panel B: Predicted Policy Effectiveness** (Preliminary)

| Highest Poverty Exposure Reductions | Predictions |
|---|---|
| San Francisco | -1.5400 |
| Minneapolis | -1.5051 |
| St. Louis | -1.4119 |
| Buffalo | -1.3245 |
| San Jose | -1.0930 |
| New Orleans | -0.9508 |
| Newark | -0.6253 |
| Louisville | -0.5819 |
| Rochester | -0.5725 |
| Baltimore | -0.5643 |

*Notes*: Panel A Column (1) presents the regression coefficients from a multivariate regression with the dependent variable being the effect of SAFMR on poverty exposure across 15 metro areas. The independent variables used in the regression are detailed in the table. Column (2) displays standardized effects of the coefficients from (1), achieved by dividing each by the standard deviation of the respective variable. Negative coefficients indicate a reduction in poverty. (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). Panel B shows that the prediction is based on the multivariate regression with the dependent variable being the effect of SAFMR on poverty exposure across 15 SAFMR-mandated metro areas. Negative coefficients indicate a reduction in poverty.

# Appendices

# Appendix A Sample Construction

Given the various variables, the original data set contains, we directly use the poverty rate in the original data to align with the HUD's standard when they are making decisions. More specifically, we find the poverty rate is constant during the year 2012 to 2017, which is defined as the percent of the population below the poverty level, in census tract (2012 and later files use Census 2010 designation). Thus, we rule out any voucher recipients introduced neighborhood change; we use the 2010 Census tract poverty rate which are those poverty rate during 2012 to 2017 in our sample. For any tracts (6,928 out of 47,635 tracts) that do not have any voucher holders before 2017, we use the first observed non-missing tract level poverty rate as their poverty level during 2011 to 2021. Only a tiny amount of household-year observations (6,340) do not have a poverty rate.

We also use the geographical code downloaded from HUD's website to determined if the household's surrounding tract are designated to HUD's metro areas for the mandatory SAFMRs adoption in FY 2019. In addition, we dropped dropped any households in mandatory metros or housing authorities that are pre-treated before the April 2018 mandatory adoption or never adopt the policy innovation (1.42 millions household-year records excluded). Several observations in certain areas are also dropped due to the following reasons. Public Housing Authorities in the mandated 24 MSAs were required to use SAFMRs, beginning no later than April 1, 2018. However, each PHA in the mandated areas still has the autonomy to choose actual adaption dates, and may not necessarily use the 100% SAFMRs as the subsidy payment standards. Thus, a few MSAs and PHAs that meet the above criteria are excluded from the treated group in our empirical 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. Second, pre-treated areas and metros are very close to the pre-treated areas are 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) are 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.[10] In other words, Pittsburgh only has two payment standards and thus we also exclude Pittsburgh, PA HUD Metro FMR Area in the treatment sample.

For our across-metro variation strategy, we define the benchmarks as follows. The first three criteria are proposed by HUD initially. We also confirmed with HUD and using their initial selection tool for the proposed rule of SAFMRs.[11] 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.[12] The rental unit vacancy rate requires a certain amount of rental units stocks in those metro areas to prevent the upward pressure on rental prices due to increase in demand of rental units in low-poverty areas without the creation of additional supply in the short run. The final rule of HUD also requires the numerator of the third requirement, 'voucher concentrated in low-opportunity neighborhoods' above 25% ('The percentage of voucher families living in concentrated low-income areas relative to all renters within the area must be at least 25 percent.'). However, almost all metros' voucher holders are concentrated in high-poverty areas compared with renters, as shown in Figure 2. Certain factors are behind the decision-making process when such thresholds are set as well as the following public comments.

Table 1 lists the MSAs that meet the above criteria and are 'de facto' selected as the mandated MSAs by HUD. The first three criteria information in Table 1 is directly downloaded from HUD (Initial Proposed Selection Tool[13]) Voucher Concentration (census track level measure) is defined as the ratio of vouchers in a concentrated-low-income area (CLIA) divided by the number of all vouchers, to the number of renter units in CLIA divided by all renter units. Concentrated low-income areas (CLIAs) are defined as those census tracts in the metropolitan FMR area with a poverty rate of 25 percent or more, or any tract in the metropolitan FMR 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). Unit Concentration (Zip Code

[10] 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.

[11] See SAFMR Proposed Rule Area Selection Tool

[12] See Kep Aspects of the Final Rule

[13] See SAFMR Proposed Rule Area Selection Tool

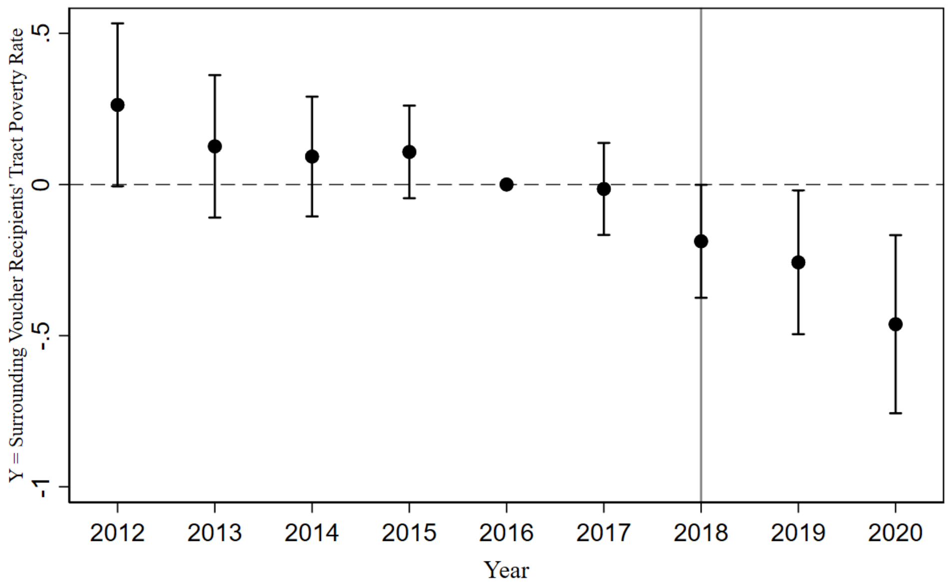
Tabulation Areas level measure) is defined as the number of units in ZCTAs with SAFMR above 110% Metro FMR divided by the number of all renter units in that ZCTA. Rental Units Vacancy Rate (metro level measure) is defined as the number of vacant for rent units divided by sum of the number of vacant for rent units, the number of renter-occupied units, and the number of rented but not occupied units. We use the 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[14], 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.[15] Thus, we combine the three initial selection parameters as well as the rental unit vacancy rate as our parameters when we selecting the comparison metros.

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

[15] See SAFMR Proposed Rule Area Selection Tool

**Figure A1: Event Study**

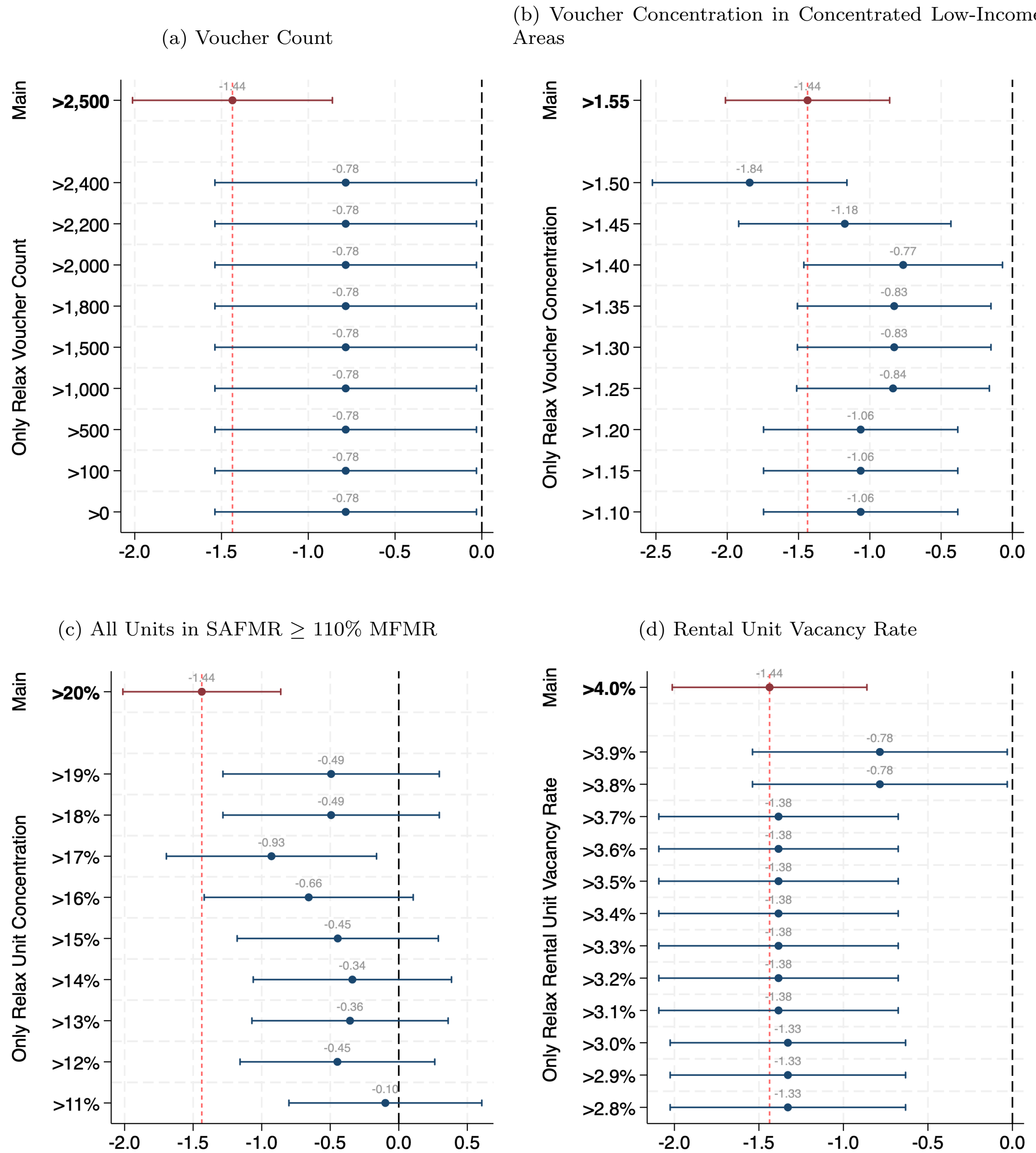



*Notes:* The event study graph plots the $\beta_t$ coefficients for all $t \in \{2012, 2020\}$ from the following regressions:

$$\mathrm{Y}_{ict} = \alpha + \Sigma_{t\in\{2012,2020\}}\beta_t \times \mathrm{Mandatory}_c \times \mathrm{Post}_t + \delta_c + \zeta_t + \epsilon_{ict}$$

where the subscripts denote household $i$ at year $t$ live in county $c$. The dependent variable is the surrounding voucher holder's tract poverty rate, $\delta_c$ denotes the county fixed effects, $\zeta_t$ denotes the calendar year-contract month fixed effects. Mandatory is equal to one if voucher holders are in the mandatory metros. Post is equal to one if the effective date of voucher holders after March 31st of 2018. Standard errors are clustered at HUD MSA-year level.

**Figure A2: Robustness Check: Leave-one-out Validation for the HUD's Selection Benchmark**

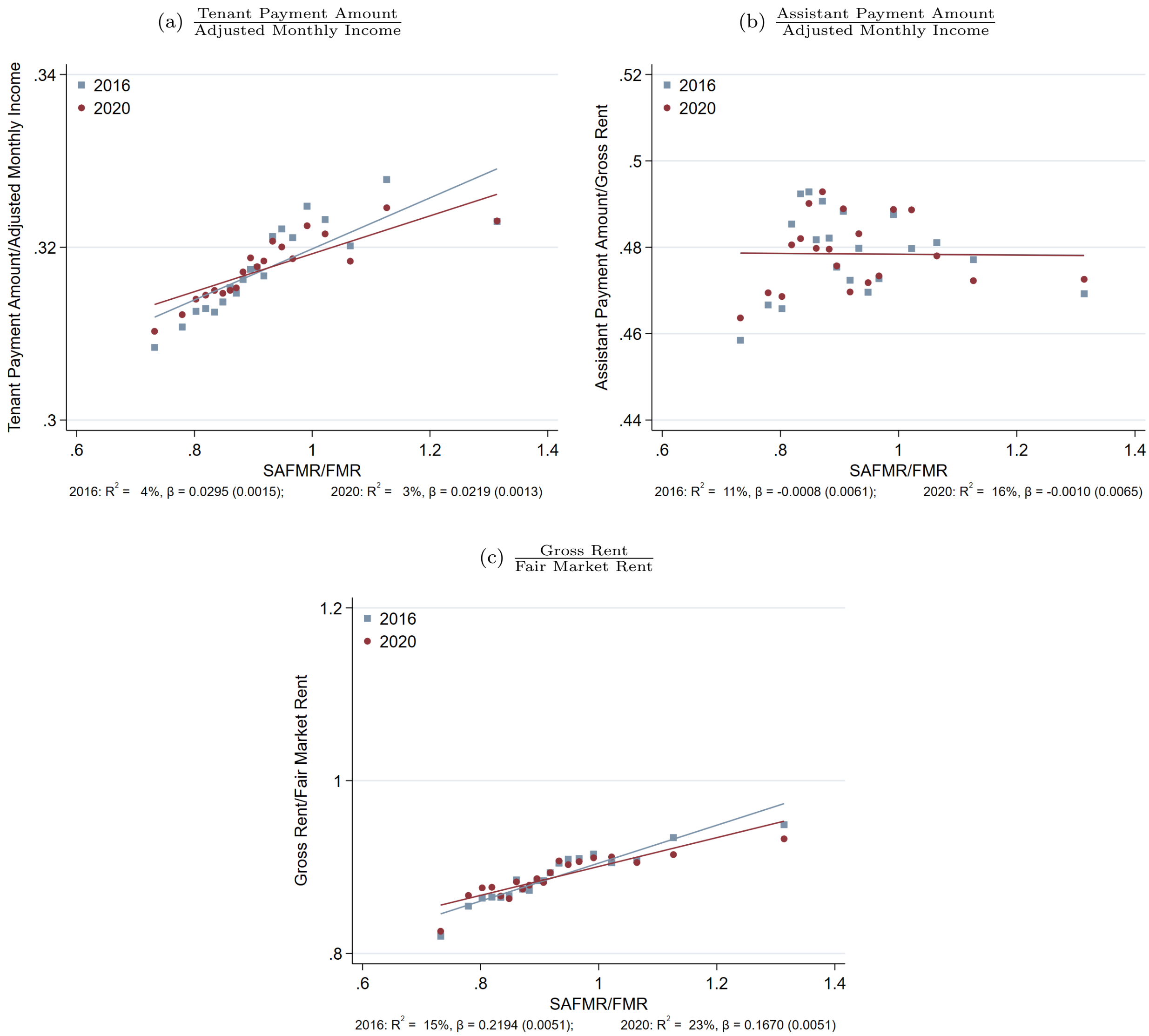



*Notes:* The figures display regression results using a control group that relaxes only one of the four HUD selection benchmarks. The regression specification is as follows:

$$Yict = \alpha + \beta \text{Mandatory}c \times \text{Post}t + \lambda \mathbf{X}' it + \delta_c + \zeta_t + \epsilon_{ict}$$

Where subscripts represent household $i$ in year $t$ residing in county $c$. $\delta_c$ stands for the county fixed effects, and $\zeta_t$ represents the calendar year fixed effects. $\mathbf{X}_{it}$ includes a set of household head-level control variables, such as race, gender, number of children, age, and household count. "Asian" encompasses both Asian and Pacific Islander categories, while "Other Race" includes Native Americans and other multi-racial identifiers. "Mandatory" is set to one if voucher holders are located in the mandatory metros. "Post" equals one if the effective date for voucher holders is after March 31st, 2018. Standard errors are clustered at the HUD MSA-year level, and bars denote the 90

**Figure A3: Attributes of Existing Voucher Holders and Neighborhood Quality: Comparison Metros**




*Notes:* The plot utilizes restricted data from 2016 and 2020, focusing solely on voucher recipient households that relocated and currently reside in the 15 mandatory metros. In Panel (a), we regressed the household-level tenant payment amount, sourced from the household, against the household-level SAFMR to FMR ratio. In Panel (b), we regressed the assistant payment amount, from the local housing authority, against the household-level SAFMR to FMR ratio. Panel (c) uses the household level gross rent to fair market rent ratio. The housing assistance payment amount and the housing assistance payment amount are adjusted to 2016 dollars. Each dot on the plot represents the mean value for one of the 20 quantiles of the ZIP code-level SAFMR/FMR distribution, conditional on the PHA-HUD metro-year for both 2016 and 2020.

**Table A1: Robustness Check: Using Alternative Control Group**

| | w/Comps | | w/All Metros | | w/Top 100 Metros | |
|---|---|---|---|---|---|---|
| Y = Poverty Rate | (1) | (2) | (3) | (4) | (5) | (6) |
| Mandatory × Post | -0.3955*** | -0.3796*** | -0.2396*** | -0.2083** | -0.2713*** | -0.2413*** |
| | (0.0929) | (0.0925) | (0.0843) | (0.0836) | (0.0855) | (0.0848) |
| Constant | 25.0191*** | 26.4180*** | 24.4766*** | 24.8696*** | 24.6100*** | 25.1789*** |
| | (0.0216) | (0.5024) | (0.0142) | (0.2461) | (0.0152) | (0.2680) |
| Year FEs | Yes | Yes | Yes | Yes | Yes | Yes |
| County FEs | Yes | Yes | Yes | Yes | Yes | Yes |
| Control Variables | No | Yes | No | Yes | No | Yes |
| *N* | 5,305,325 | 5,305,325 | 12,222,003 | 12,222,003 | 11,100,156 | 11,100,156 |

*Notes:* Columns (1) and (2) report the regression results using our 15 comparison metros as the control group. In contrast, columns (3) and (4) report the regression results using the all the remaining households as the control group in our original data, while columns (5) and (6) report the results of the sample using the top 100 metros (by number of voucher holders in 2016) as the control group. The regression specification is as follows:

$$\mathrm{Y}_{ict} = \alpha + \beta \mathrm{Mandatory}_c \times \mathrm{Post}_t + \lambda \mathbf{X}'_{it} + \delta_c + \zeta_t + \epsilon_{ict}$$

where the subscripts denote household $i$ at year $t$ live in county $c$. $\delta_c$ denotes the county fixed effects, $\zeta_t$ denotes the calendar year fixed effects. $\mathbf{X}_{it}$ indicates a set of household head-level control variables such as race, gender, number of children, age, and the number of households. Asian includes Asian and Pacific Islander, and Other Race includes Native Americans and other multi-race headers. Mandatory is equal to one if voucher holders are in the mandatory metros. Post is equal to one if the effective date of voucher holders after March 31st of 2018. Standard errors are clustered at county-year and presented in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

**Table A2: Robustness Check: Using Calendar Year as the Post Treatment Indicator**

**Panel A: Using All Recipients Sample**

| Y = | Poverty Rate | | <20% Poverty | | <10% Poverty | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Mandatory × Post | -0.4031*** | -0.3774*** | 0.0137*** | 0.0129*** | 0.0081*** | 0.0074*** |
| | (0.0955) | (0.0926) | (0.0027) | (0.0026) | (0.0016) | (0.0016) |
| Constant | 25.0227*** | 26.4415*** | 0.4037*** | 0.3944*** | 0.1486*** | 0.1491*** |
| | (0.0219) | (0.5462) | (0.0006) | (0.0115) | (0.0003) | (0.0052) |
| Year FEs | Yes | Yes | Yes | Yes | Yes | Yes |
| County FEs | Yes | Yes | Yes | Yes | Yes | Yes |
| Control Variables | No | Yes | No | Yes | No | Yes |
| $N$ | 5,305,325 | 5,305,325 | 5,305,325 | 5,305,325 | 5,305,325 | 5,305,325 |

**Panel B: Using First Time Recipients Sample**

| Y = | Poverty Rate | | <20% Poverty | | <10% Poverty | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Mandatory × Post | -0.7230** | -0.7187** | 0.0310*** | 0.0303*** | 0.0295*** | 0.0288*** |
| | (0.3477) | (0.3471) | (0.0111) | (0.0108) | (0.0067) | (0.0067) |
| Constant | 26.2455*** | 26.4751*** | 0.3834*** | 0.3928*** | 0.1380*** | 0.1499*** |
| | (0.0950) | (0.4160) | (0.0031) | (0.0100) | (0.0019) | (0.0074) |
| Year FEs | Yes | Yes | Yes | Yes | Yes | Yes |
| County FEs | Yes | Yes | Yes | Yes | Yes | Yes |
| Control Variables | No | Yes | No | Yes | No | Yes |
| $N$ | 362,059 | 362,059 | 362,059 | 362,059 | 362,059 | 362,059 |

*Notes:* Columns (1) and (2) report the regression results with the dependent variable as the 2010 level of poverty rate of a census tract. In contrast, columns (3) and (4) feature a binary variable indicating whether household $i$ lives in a census tract with a poverty rate below 20%, while columns (5) and (6) report a binary variable indicating whether household $i$ lives in a census tract with a poverty rate below 10%. The regression specification is as follows:

$$\mathrm{Y}_{ict} = \alpha + \beta \mathrm{Mandatory}_c \times \mathrm{Post}_t + \lambda \mathbf{X}'_{it} + \delta_c + \zeta_t + \epsilon_{ict}$$

where the subscripts denote household $i$ at year $t$ live in county $c$. $\delta_c$ denotes the county fixed effects, $\zeta_t$ denotes the calendar year fixed effects. $\mathbf{X}_{it}$ indicates a set of household head-level control variables such as race, gender, number of children, age, and the number of households. Asian includes Asian and Pacific Islander, and Other Race includes Native Americans and other multi-race headers. Mandatory is equal to one if voucher holders are in the mandatory metros. Post is equal to one if calendar year is later than 2018. Standard errors are clustered at HUD MSA-year and presented in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).