

Pricing for Opportunity: The Impact of Spatially Varying Rent Subsidies on Housing Voucher Neighborhoods and Take-up

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Abstract

The Housing Choice Voucher program serves over 2.3 million households per year. While the program provides significant benefits, most voucher holders live in high-poverty neighborhoods, and many recipients fail to use their vouchers at all. This paper evaluates a new programmatic approach for expanding and improving neighborhood outcomes, which pegs voucher subsidy amounts to ZIP Code-level rents, rather than being uniform across an entire metro area. We find that this pricing change increases moves to higher rent, lower poverty ZIP Codes without increasing overall financial costs or affecting the ability of new voucher recipients to use their vouchers to lease homes. This even holds true for the recipients most at risk of experiencing a decline in their ability to use vouchers because the stock of voucher-eligible units near them likely decreases. We show that subgroups of households and landlords make adjustments on other margins, however. Specifically, those leasing in low-rent neighborhoods rent smaller homes and spend more of their income on rent, while landlords in these neighborhoods charge lower rents to match rent subsidies.

Keywords: Housing vouchers; mobility; subsidy pricing; administrative burden

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1 Introduction

Research shows that young, low-income children benefit greatly from living in low-poverty neighborhoods, but their families face significant barriers to moving to such neighborhoods (Chyn and Katz, 2021; Chetty and Hendren, 2018; Chyn, 2018; Chetty et al., 2016). While providing housing assistance through portable, tenant-based vouchers should theoretically open up more neighborhood options for families, the nation’s largest federal voucher program has fallen short in delivering on that promise. On average, housing choice voucher holders live in neighborhoods that look very similar to those where other poor households live (Pendall, 2000; Wood et al., 2008; Galvez, 2011). More fundamentally, many voucher recipients fail to use their voucher in any neighborhood. Recent estimates suggest that about only about 60 percent of households that receive a voucher successfully use it to lease a home within six months (Ellen et al., 2024).

One possible reason that vouchers are not opening up more neighborhoods is that the subsidy that vouchers provide is too flat, with voucher rent ceilings or payment standards set at the same level across an entire metropolitan area. With uniform, metropolitan-wide rent ceilings, subsidies tend to be generous in low-rent neighborhoods, but inadequate to cover rents in high-rent neighborhoods. As a result of this uniform subsidy price, homes affordable to voucher recipients are concentrated in low-rent neighborhoods.

In response to this limitation, in 2018, the U.S. Department of Housing and Urban Development (HUD) mandated a programmatic reform in selected metropolitan areas that makes voucher rent ceilings or payment standards vary with ZIP Code rents. We test whether this reform enabled more voucher recipients to move to lower poverty, higher opportunity areas. We also examine whether the pricing change affected the ability of recipients to use their vouchers. At the time the rule was proposed, several advocacy groups expressed concerns that the change would reduce landlord voucher acceptance in low-rent ZIP Codes, where the new payment standards would be below the subsidies to which landlords were accustomed and where voucher holders typically live (National Low Income Housing Coalition, 2022). In other words, while increasing subsidies in high-rent neighborhoods should broaden the choice set, reducing subsidies in low-rent neighborhoods could increase search costs for many voucher recipients and reduce the already low voucher leasing success rates.

Our research design exploits the criteria used by HUD to select the 23 metropolitan areas mandated to use ZIP Code-level rent subsidies. Our comparison group comprises voucher recipients in metropolitan areas just below the threshold HUD used for inclusion. Specifically, we estimate difference-in-difference regressions, comparing changes in outcomes for new voucher recipients at public housing agencies (PHAs) mandated to use ZIP Code-

level subsidies in 2018 with changes for new recipients at PHAs in metropolitan areas that fell just below the selection threshold. We use unique HUD administrative data for all voucher recipients from 200 housing authorities, from 2014 through 2022, which include key demographics, destination address, as well as origin ZIP Code. This novel dataset allows us to measure leasing success rates for voucher recipients, a key metric that prior research has been unable to track.

We find that the shift to neighborhood-varying rent subsidies was effective in the primary goal of improving locational outcomes for voucher recipients. The pricing change increased the share of new voucher holders moving to neighborhoods with higher rents and lower poverty rate percentiles as compared to their origin neighborhoods. Four years after implementation, successful voucher households in treated metropolitan areas experienced a reduction in neighborhood poverty rate percentile that was nearly four percentile points greater than their counterparts in comparison metropolitan areas. This effect size is substantial: our treatment effect is around half of the treatment effect of the Moving to Opportunity (MTO) experiment (Quigley et al., 2008), despite the fact that this intervention did not come with MTO’s requirement that households use their vouchers in a lower poverty neighborhood, which contributed to a 14 percentage point decline in the share of households successfully using their vouchers (Shroder, 2002). The effect on access to higher-rent neighborhoods appears larger for families with children.

Meanwhile, we see no evidence that the adoption of ZIP Code rent subsidies affected the share of new recipients able to use their vouchers (success rates), though estimates are somewhat noisy. Even for the voucher recipients originating in low-rent neighborhoods (where the pool of eligible units nearby likely shrank), and those receiving vouchers from PHAs disproportionately serving such neighborhoods, we see no decline in success rates relative to the comparison group. That said, we find some weak evidence that ZIP Code-level rent subsidies reduced successful lease-up rates for Hispanic voucher recipients.

Another concern with the change in subsidy limits is increased fiscal costs. If more recipients lease up in ZIP Codes where ceiling rents increased, it may cost housing authorities more per household, potentially reducing the number of households served. We do not find evidence of increased costs per household; while the costs of serving households in high-rent neighborhoods increased, this was offset by a decline in the costs of serving households in low-rent neighborhoods, who still constitute the majority of new voucher recipients.

Taken together, these results show that setting subsidy limits at the ZIP Code level helped new voucher recipients move to a broader set of neighborhoods, without a corresponding trade-off in the form of depressed voucher success rates or increased subsidy costs to housing authorities. We explore other margin of adjustments as well.

One potential margin of adjustment is rent-to-income ratios, or rent burdens faced by voucher recipients. While we found no significant increase in rent burdens overall, recipients who lease homes in low-rent neighborhoods after Small Area FMR adoption have rent-to-income ratios that are 1 percentage point higher than the comparison group, which represents a 3 percent increase over baseline. There is a similarly sized decrease in rent-to-income ratios in higher-rent ZIP Codes. These greater rent burdens in low-rent neighborhoods may raise distributional concerns, particularly if some households face greater barriers in renting homes in high-rent neighborhoods.

A second potential margin of adjustment is unit size. After the adoption of ZIP Code-level subsidies, voucher recipients renting homes in low-rent neighborhoods were less likely to rent homes larger than the ones for which they qualified. A third margin relates to gross rents. The rents charged for units occupied by new voucher recipients in low-rent neighborhoods also declined after the switch from uniform to ZIP Code-level subsidies. About one third of this decline can be attributed to landlords lowering their rents to match payment standards, as opposed to voucher recipients simply renting smaller or lower quality homes, or renting homes in more affordable census tracts within lower rent ZIP Codes. Conversely, gross rents charged to voucher holders in high-rent neighborhoods increased. A final margin was moves outside of PHA service areas. We find that after the adoption of ZIP Code-level subsidies, households receiving vouchers from PHAs serving predominantly low-rent neighborhoods—in other words, PHAs that likely saw a large decline in the quantity of voucher-eligible units within their service area—were more likely to rent homes outside of their PHA’s service area.

This paper contributes to multiple strands of literature. First, this paper adds evidence on the effects of uniform versus adjusted subsidy pricing, which is important across multiple social programs (Christensen and Bronchetti, 2020; Bronchetti et al., 2019). We specifically add to a small but growing literature on housing voucher rent subsidies. A few papers study the adoption of ZIP Code-level subsidies in five housing authorities selected for a 2012 demonstration and an earlier adoption of such subsidies in Dallas, and find they were successful in encouraging moves to lower poverty neighborhoods (Collinson and Ganong, 2018; Dastrup et al., 2018, 2019; Reina, 2019; Park, 2024). Research also found large differences across the small number of housing authorities that were early to adopt ZIP Code-level subsidies that warrant further investigation. We are among the first to study effects of the most recent version of ZIP Code-level subsidies (Eriksen et al. (2024) study effects on poverty exposure), across an expansive sample of nearly 90 housing authorities.

Second, and perhaps most uniquely, we are the first to estimate the effect of ZIP Code-level subsidies on voucher take-up, which was a key concern when the rule was passed. While there is a large literature on administrative burden and program participation (Ko

and Moffitt, 2020; Herd and Moynihan, 2018), very little of this work studies housing assistance, despite the heightened challenges for take-up that the program poses. This gap is predominately due to a historical lack of consistent, representative data. We use unique administrative data from HUD to measure voucher success rates and search times, contributing to a relatively limited body of work on the drivers of voucher success rates (Ellen et al., 2024); this is among the first papers to evaluate how programmatic reforms can affect voucher take-up.

Lastly, we add to the broader literature on strategies to expand neighborhood choice and access. We study a cost-neutral (or at least low-cost) strategy to help voucher holders reach low-poverty neighborhoods. Bergman et al. (2024); DeLuca et al. (2023) show that housing search frictions are a key driver of income segregation, and that high-touch, customized search support significantly increases the share of voucher families moving to high-opportunity neighborhoods. The original Moving to Opportunity Demonstration achieved its mobility results primarily through an alternative approach—restricting voucher use to lower poverty neighborhoods, though this came at the cost of lower voucher success rates (Chetty et al., 2016).

The paper proceeds as follows. Section 2 details the institutional context of the voucher program. Section 3 describes the data used for the study, and section 4 describes the differences-in-differences identification strategy. Section 5 presents results on the effects of ZIP Code-level rent subsidies on locational outcomes, success rates, programmatic costs, and other margins of adjustment. Section 6 concludes.

2 Background

Each year, over 2.3 million low-income households use housing choice vouchers to help cover the rent of private market homes (Center on Budget and Policy Priorities, 2022). If voucher holders rent units at or below a specified local payment standard, they pay 30% of their income in rent. Voucher holders can opt for units with rents above the payment standard, but they have to pay any amount by which the rent exceeds the payment standard.¹

Research shows that the voucher program reduces the rent burdens of recipients, leads them to less crowded homes, lowers their likelihood of homelessness, and even improves their children’s performance in school (Mills et al., 2006; Schwartz et al., 2020). Yet the program has had less success in helping households reach a broader set of neighborhoods (McClure and Johnson, 2015; Pendall, 2000; Wood et al., 2008; Galvez, 2011). Relative to other poor households, voucher holders live in neighborhoods with similar poverty rates and

¹The share of their income going to rent cannot exceed 40 percent when they first occupy a home.

racial compositions (Galvez, 2011) and near to schools that are even lower performing (Horn et al., 2014).

HUD’s method of setting Fair Market Rents (FMRs), which local housing authorities use to set the maximum local payment standard or rent ceiling, is often blamed for causing the spatial concentration of voucher holders.² FMRs have traditionally been set at roughly the 40th percentile of rents in the metropolitan area (or the county outside of metropolitan areas), which means that payment standards tend to be too low to cover most housing in low-poverty neighborhoods.³ In the case of Dallas, for example, Collinson and Ganong (2018) report that under 2013 metro-wide FMRs, vouchers covered the cost of 68 percent of homes in the lowest rent neighborhoods but only 15 percent of homes in higher-rent neighborhoods.

In 2001, to address concerns about spatial concentration of voucher holders, HUD began setting the metro-wide FMR at the 50th percentile in a set of markets where voucher households were particularly concentrated in a limited set of neighborhoods. While the goal was to enable greater neighborhood choice, raising payment standards in all neighborhoods created some countervailing incentives. Most concerning is that landlords might capture most or all of the higher subsidies, by increasing the rents they charge. Given that tenants pay a fixed share of their income in rent, these increases in rent would be borne entirely by the government, thus increasing programmatic costs. Indeed, Collinson and Ganong (2018) show that the increases in payment standards were primarily captured by landlords through higher rents, with no noticeable increase in unit (or neighborhood) quality.

In 2009, HUD began developing more granular FMRs for lower levels of geography (Bibler et al., 2019). These Small Area FMRs (SAFMRs) vary across ZIP Codes, depending on the ratio of the median rent for a two-bedroom unit in the ZIP Code to the median two-bedroom rent in the metropolitan area. Setting FMRs at the ZIP Code level means higher payment standards in higher-rent (generally lower poverty) neighborhoods and lower payment standards in lower rent neighborhoods. Small Area FMRs were first implemented by two housing authorities in Dallas, TX, as part of a court settlement in 2011. HUD then launched a demonstration expanding use to five additional housing authorities in 2012.⁴

Collinson and Ganong (2018) find that moving from uniform rent subsidies to ZIP Code rent subsidies in Dallas significantly increased the share of voucher holders living in low-poverty areas, without increasing costs per voucher household. Similarly, the HUD-supported

²Local housing authorities can set payment standards between 90 and 110 percent of the applicable FMR.

³HUD sets Fair Market Rents (FMRs) at the 40th percentile of gross rent for standard quality units occupied by recent movers in the local market.

⁴The five PHAs were: Chattanooga Housing Authority (TN); Housing Authority of Cook County (IL); Housing Authority of the City of Laredo (TX); Housing Authority of the City of Long Beach (CA); and the Town of Mamaroneck Housing Authority (NY).

evaluation of the adoption of Small Area FMRs in Dallas and the five additional PHAs found that moves to higher rent and higher opportunity neighborhoods increased among both new recipients and existing voucher households, relative to the comparison group (Dastrup et al., 2018). Effects were most robust for PHAs in the Dallas metropolitan area, though effects remained significant when Dallas PHAs were removed from the sample. Results were stronger for existing voucher holders and for households with children (Dastrup et al., 2019). Using a different comparison group and a shorter follow-up period, Reina et al. (2019) found substantial variation across the PHAs and found that the shift to ZIP Code rent subsidies only encouraged moves to higher rent neighborhoods in Dallas. This has led some to question the generalizability of the Dallas location results⁵, especially given the involvement of a local nonprofit in Dallas that provided counseling services to voucher recipients moving to higher opportunity areas (Reina et al., 2019).⁶ Eriksen et al. (2024) also report substantial heterogeneity across metropolitan areas. An additional troubling finding from the final evaluation was that rent burdens of voucher holders increased (relative to the comparison group) with significant increases for voucher households residing in low-rent ZIP Codes (Dastrup et al., 2018). Numerous comments submitted as part of the rule making process raised concerns over the potential for greater costs (to tenants and to PHAs) in other places.

In November of 2016, HUD issued a final rule mandating that 23 named metropolitan areas (in addition to Dallas) would be required to adopt Small Area FMRs in October of 2017.⁷ Two months before this deadline, the Trump administration announced a two-year delay to implementation, but the D.C. District court overturned this delay on December 23, 2017, and HUD required that implementation begin on April 1, 2018. On October 23, 2023, HUD announced that an additional 41 metropolitan areas would be required to start using Small Area FMRs by the end of 2024. This expansion means that 45 percent of households using vouchers are now covered by Small Area FMRs.⁸

2.1 Hypothesized impacts

In this paper, we consider the impacts of shifting to geographically targeted rent ceilings on two key outcomes of the housing search process for voucher recipients: first, the likelihood

⁵Several comments submitted during the public comment period on the proposed rule raised concerns about generalizing the Dallas findings.

⁶PHA staff in Dallas interviewed as part of the final evaluation also reported large declines in success rates, but evaluators were unable to assess if this was caused by SAFMRs (Dastrup et al., 2018).

⁷Details on how this rule differs from the version of Small Area FMRs implemented in the demonstration can be found in online appendix A.

⁸See https://www.hud.gov/press/press_releases_media_advisories/hud.no.23.242 for more details.

that a household is able to use their voucher at all, or their probability of leasing up, and second, the utility that they derive from the home that they lease with their voucher, given that they are able to find a match, or match quality. Households derive utility from the neighborhood where they lease up, features of the home such as unit size and quality⁹, and the non-housing consumption allowed through lower rent burdens.

Under uniform rent ceilings, the share of units that fall within the rent ceiling varies across neighborhoods, with a higher share of units affordable to program participants in lower rent areas. In fact, rent ceilings are likely to be above market rents in lower rent areas, making voucher recipients very attractive to landlords. Landlords in these neighborhoods can charge above-market rents to voucher recipients, as the voucher holder's contribution to rent is capped at 30 percent of their income and unaffected by the rental price of a unit, up to the rent ceiling.

In conducting their housing search, voucher recipients therefore face several tradeoffs: if they focus their search in higher rent neighborhoods, their probability of finding a voucher-affordable unit, and thus being able to use the voucher, will be lower. Further, to the extent that voucher recipients find eligible units in higher rent areas, they are likely to be smaller or lower quality than those within the payment ceiling in lower-rent neighborhoods, and/or to charge rents above the metro-wide payment standard, and thus require voucher recipients to pay more than 30 percent of their income on rent. (Recall that if a unit's rent is above the rent ceiling, voucher holders must pay the marginal difference out-of-pocket).

The Small Area FMR policy change, which involves tilting payment standards to align with ZIP Code rent levels, changes these trade-offs. In high rent areas, moving from uniform rent subsidies to Small Area FMRs will increase rent ceilings, which should increase the share of homes that are eligible for the program and may increase lease-up probabilities for households who search in these areas. This could also permit households to access larger or higher quality homes than they could under uniform payment ceilings. Rent burdens may also now be lower for voucher holders who lease homes in high-rent neighborhoods, as more households will be able to find units with rents at or below the rent ceiling.

In low-rent areas, by contrast, ZIP Code level payment standards will reduce rent ceilings. This should decrease the number of eligible units and therefore lower the probability that a household will be able to use their voucher in these neighborhoods. Landlords operating in these neighborhoods who still wish to rent to voucher holders may have to lower the rents charged to voucher holders to remain in line with payment standards. The lower rents could also disincentivize landlords from participating in the program at all, if they no longer

⁹Note that while units must pass a minimum housing quality standard inspection, there can still be variation in housing quality for voucher recipients.

perceive a financial benefit from renting to voucher holders (National Low Income Housing Coalition, 2022).¹⁰

This poses a serious concern, as the majority of voucher recipients begin their searches in such neighborhoods. Further, households who still choose to use their voucher in areas where rent ceilings have declined will receive smaller subsidies, which may lead them to rent smaller or lower quality homes. The lower rent ceiling could also lead more households to lease homes with rents that are higher than the ZIP Code rent ceiling, increasing the share of their income going to rent.

In sum, shifting to ZIP Code level rent subsidies should expand housing options in higher rent neighborhoods while decreasing them in lower rent areas and lead, in turn, to an increase in the share of voucher holders who lease in higher rent ZIP Codes, but there may be a decline in new recipients' ability to use their voucher at all. Recipients leasing in lower rent neighborhoods may rent units that are smaller or of lower quality, or that come with higher out-of pocket costs, than recipients in the same neighborhoods under uniform payment standards, while the opposite may be true for households leasing in higher rent neighborhoods.

The changes in the relative neighborhood trade-offs may lead to distributional concerns. Households who start their search in low-rent neighborhoods should be most at risk of declines in lease-up probability and welfare losses, as the pool of eligible units in their neighborhood shrinks; similarly, households who receive their vouchers from PHAs that predominantly serve low-rent ZIP Codes may struggle to use their vouchers as the number of eligible units in the PHA service area declines. These households also face higher search costs in order to take advantage of higher payment standards, as they may have to search outside of their origin neighborhoods, or outside of their issuing PHA's service area altogether.

Other households may face heightened barriers to moving to higher-rent neighborhoods. Black and Hispanic households, for example, who more frequently live in low-rent neighborhoods, may face higher search costs under spatially varying subsidies, which can raise concerns both about the ability to use their vouchers and their ability to make upwardly-mobile moves. Households of color may also have to live in areas with larger white populations in order to move to a neighborhood where rent ceilings have increased.

Lastly, we may expect heterogeneity in effects by household composition and size. Younger households and households with kids may be more motivated to move to higher opportu-

¹⁰These effects could be mitigated by the fact that uniform payment standards are not always binding, however. Prior to the intervention, many voucher recipients in low-rent neighborhoods leased units with rents that were below the uniform rent ceiling, perhaps due in part to the rent reasonableness tests conducted by housing authorities, which aim to keep the rents charged to voucher holders in line with rents for similar units that are rented to unassisted households.

nity neighborhoods, particularly to neighborhoods with better schools or higher-paying jobs. There may be push factors from low-cost neighborhoods as well, particularly for larger households, as the unit-size tradeoff between low-rent and high-rent neighborhoods will be altered, with larger homes now relatively less affordable or available in low-rent neighborhoods where payment standards declined.

3 Data

3.1 Administrative data on voucher use

This study draws on individual-level, administrative data on voucher issuance, lease up, and neighborhood locations (U.S. Department of Housing and Urban Development, 2023). PHAs are required to report every programmatic action for each voucher recipient to HUD’s Office of Public and Indian Housing Information Center (PIC). We use three types of information drawn from the PIC data: voucher issuance actions, new admissions actions, and an annual cross-sectional database of voucher holders. We are the first researchers to use administrative data to measure lease-up rates; the few existing studies of lease-up have focused on much smaller samples of PHAs that involve original data collection (Chyn et al., 2019; Finkel and Buron, 2001).

A search event begins with the issuance of a search voucher, and ends either when the household successfully leases up, or fails to secure a home. When a search voucher is issued, we observe key demographic variables, including the race, ethnicity, age, disability status, and citizenship status of the head of household, as well as the size of the household. Importantly, we also observe the ZIP Code where the household was residing at the time of receiving a search voucher.

The new admissions data contain actions that represent leasing up into the program, including the date a household rents a home with their voucher, and the address of that home. We use data from 2014 through the first half of 2022, which allows us to calculate success rates for 2015 through 2021, permitting time for longer searches to conclude. We use the annual cross-sectional database of voucher holders to distinguish new entrants to the voucher program (the focus of this study) from existing voucher holders looking to move.

We track several outcomes. Our first set of outcomes examines the characteristics of the neighborhoods reached by those new voucher recipients who are successful in their search, relative to the characteristics of the ZIP Codes where they originate, drawing mostly on five-year, 2015-2019 ACS data. Our second set of outcomes focuses on housing search, including leasing success and search time. When estimating leasing success rates, we use a one-year

search interval to ensure consistency across years, as almost all successful searches (99% in our sample) are completed within a year. Search time is the elapsed time between receiving a search voucher and leasing up into the program for households that are successful in their search. While PHAs are required to allow 60 days for a household to search, in practice, most households are given much longer, and search time can vary widely across individuals and markets. For households who are successful in using their vouchers, we also observe the portion of the rent paid by the household and the housing authority, and household rent-to-income ratios.¹¹ We also observe a limited set of details on the home that successful voucher recipients rent, including the gross rent and the number of bedrooms.

3.2 Small Area FMRs and Metro Area FMRs

HUD releases FMRs annually according to their fiscal calendar, with new FMRs generally going into effect on October 1 of each year (U.S. Department of Housing and Urban Development, 2022b,a). Prior to 2018, HUD released hypothetical Small Area FMRs for all ZIP Codes within metropolitan areas¹², even though only a handful of local housing agencies used them to set actual payment standards. For each search event, we identify the applicable Small Area FMR, the Metro Area FMR, and the ratio of the two for the ZIP Code where the voucher recipient lives when their search voucher is issued (rent ratio).¹³ This rent ratio variable captures the median rent of a recently occupied two-bedroom units in the ZIP Code relative to the median rent of recently occupied two-bedroom units in the overall metropolitan area. For successful searches, we conduct the same matching using the ZIP Code where the voucher holder leases up.¹⁴ We use the identified Metro Area FMR to calculate the rent ratio in destination neighborhoods. Our main specifications use time-varying FMRs (matched at the time of voucher issuance), but our results are very similar if we use 2017 FMRs, to avoid any potential changes to FMRs induced by the policy.

Throughout the paper, we define low-rent ZIP Codes as ZIP Codes where the Small Area

¹¹Some variables are recorded only in the longitudinal data, and not the new admissions data. For models on tenant rent contributions and rent-to-income ratios, we use only households that we observe in the longitudinal data on the day of admission; this consists of roughly 70% of our sample. Our core results are very consistent using this sample as well.

¹²Due to a lack of sufficient data, HUD does not calculate Small Area FMRs in non-metropolitan counties; see <https://www.huduser.gov/portal/datasets/fmr/fmr2016p/SAFMR-Proposed-Rule-FAQ.pdf> for more details.

¹³Most ZIP Codes fall entirely within one metropolitan area. In those cases, search events are also matched to the applicable Metro Area FMR based on their ZIP Code. For the few ZIP Codes that crosses metropolitan area lines, searches from that ZIP Code are assigned to the metropolitan area that houses most of the vouchers from the associated PHA.

¹⁴For the Metro Area FMR, we match first on the ZIP Code to Metro Area FMR crosswalk. If a ZIP Code crosses over multiple metropolitan areas, we use the county recorded in the cross-sectional database. If the county is missing, we use the same crosswalk that we use for the origin match.

FMR is at least 5 percent lower than the Metro Area FMR. Moderate rent ZIP Codes are ZIP Codes where the Small Area FMR is within 95-105 percent of the Metro Area FMR; high rent ZIP Codes consist of the remainder of ZIP Codes, where the Small Area FMR is more than 5 percent greater than the Metro Area FMR.

3.3 ZIP Code Tabulation Area variables

Throughout the paper, we use ZIP Codes to proxy for neighborhoods. Specifically, we link ZIP Codes to ZIP Code Tabulation Areas (ZCTAs) in order to describe the ZIP Codes where voucher recipients originate and where they lease up, using data from the American Community Survey (ACS). Most ZIP Codes in our dataset are coterminous with a ZCTA, but some ZIP Codes do not directly correspond to a ZCTA.¹⁵ These observations may be institutional addresses, which can sometimes be used for households experiencing homelessness at the time of receiving a search voucher. If the ZIP Code where a voucher recipient originates or lands can not be linked to a ZCTA, we drop that voucher recipient from our sample.¹⁶

We use the 5-year ACS data from 2015-2019 to measure neighborhood demographics, including the poverty rate and racial composition (U.S. Census Bureau, 2020). For successful searches, we consider two continuous neighborhood change outcomes: the difference between origin and destination ZIP Codes in relative rents and poverty rate percentiles. We measure poverty rate percentiles as the percentile of ZCTA poverty rates within the metro area. We measure relative rents by the ratio of the Small Area FMR estimated for the ZIP Code and the applicable metro area FMR. Note that given how Small Area FMRs are calculated, this rent ratio is essentially the ratio of median rent for a two-bedroom unit in the ZIP Code and the median rent for a two-bedroom rent in the metropolitan area as a whole.

We focus on the difference between origin and destination neighborhoods and not just the characteristics of destination neighborhoods because Small Area FMRs may change not only where voucher households are able to rent homes but also the composition of who succeeds in leasing up, and even, over the longer-run, who applies to receive vouchers. Specifically, Small Area FMRs may make it easier for voucher recipients coming from origin neighborhoods with higher rents and lower poverty percentiles to use their vouchers and make it more difficult for those coming from more disadvantaged neighborhoods. If so, a greater likelihood of leasing up in higher rent neighborhoods after implementing Small Area FMRs (for example) could arise from more voucher recipients originating in high rent neighborhoods. Our locational

¹⁵The census creates ZCTAs from underlying census blocks, so sometimes boundaries can diverge when census blocks cross ZIP Codes.

¹⁶1.4% of observations are in a ZIP Code that does not correspond to a ZCTA.

outcomes capture the extent to which individuals are able to make upwardly mobile moves (or avoid downwardly mobile moves) from their origin neighborhoods. In addition to these continuous measures comparing origin and destination neighborhoods, we also create a set of indicator variables that capture when voucher holders lease homes in more advantaged neighborhoods (i.e., with higher rents and lower poverty percentiles) and less advantaged neighborhoods (i.e., with lower rents and higher poverty percentiles).

Finally, we check if our key findings are robust to defining neighborhood outcomes based simply on the attributes of destination neighborhoods, including rent level, poverty rate, and the Opportunity Atlas measure of opportunities provided for economic mobility.

3.4 Public Housing Authority service areas

We calculate and use PHA service areas to identify PHAs that disproportionately serve low-rent neighborhoods (Tauber et al., 2024).¹⁷ Specifically, we identify ZIP Codes in each PHA service area that would have seen a change in FMRs of more than five percent in switching from uniform, metro-wide FMRs to ZIP Code-specific FMRs. We then use 2015-2019 ACS data to count the estimated number of rental units in these ZIP Codes as a fraction of the total number of rental units in the service area. The histogram on the left of online appendix figure B1 shows the distribution of these shares for declines, for our treated PHAs. We define PHAs as primarily serving low-rent areas if they are in the top tercile of PHAs in seeing rent declines as a result of the switch to Small Area FMRs.

Additionally, we use these defined service areas to construct a variable that measures the level of rent dispersion within each PHA’s service area. This variable serves as a way to measure each PHA’s “dosage” of the treatment. In service areas where rents are relatively flat, Small Area FMRs may not result in large changes in payment standards. PHAs with high levels of rent dispersion may see greater changes in payment standards across neighborhoods and are hence more exposed to the treatment. To measure dosage, we calculate the ratio of the 90th percentile of Small Area FMRs (measured at the ZIP Code level, weighted by the number of voucher holders in each ZIP Code, prior to the implementation of ZIP Code-level subsidies) to the 10th percentile of Small Area FMRs for each PHA. We define “high dosage” PHAs as those with the highest levels of rent dispersion (in the top quartile), and “low dosage” PHAs as those with the lowest level (in the bottom quartile).

¹⁷More information on PHA service areas can be found in online appendix B.

4 Methods

4.1 Identifying treatment and comparison groups

As noted, Small Area FMRs were implemented in 23 HUD-defined metropolitan areas, plus Dallas.¹⁸ HUD only considered metropolitan areas with more than 2,500 voucher holders for Small Area FMR implementation. Additionally, HUD selected metropolitan areas for participation based on four criteria:¹⁹

1. Voucher concentration (VC): the percentage of renters with vouchers in the metropolitan area living in concentrated low-income census tracts²⁰ relative to the percentage of all renters in the metropolitan area living within these areas (**threshold >1.55**)
2. Out-of-reach rental units (SAFMR110): the percentage of all rental units in ZIP Codes where the Small Area FMR is greater than 110% of the metro area FMR (**threshold >20%**)
3. Percentage in low-income areas (PLI): the percentage of voucher holders living in concentrated low-income census tracts (**threshold >25%**)
4. Rental vacancy rate (**threshold >4%**)

Using these criteria, which HUD published for each metro area during the rule-making process (U.S. Department of Housing and Urban Development, 2016), we assembled a comparison group of PHAs in metropolitan areas that were just below the threshold for inclusion. HUD set the PLI and vacancy rate thresholds on the far tails of each respective distribution, so the thresholds simply remove a few outlier metros that fall below the thresholds. Thus we consider only metro areas that pass the PLI and vacancy rate thresholds and have over 2,500 voucher recipients; we then rely only on the voucher concentration and SAFMR110 metrics to identify metropolitan areas that were on the edge of inclusion. Our comparison

¹⁸HUD uses OMB-defined, Metropolitan Statistical Areas to set metropolitan area fair market rents for some areas, but it uses smaller “HUD FMR areas,” comprising a smaller number of counties, for other areas. Of the 23 areas selected for Small Area FMRs, only six are full metropolitan areas. Three of the 24 are metropolitan divisions, and the remaining 14 consist of one or more counties within an MSA that have been subdivided into a HUD FMR area. Consistent with HUD’s approach, we use the general term metropolitan area to describe all of these areas.

¹⁹The first two criteria were included in HUD’s proposed rule, with the specific thresholds left unspecified. The second two thresholds were added to the final rule in response to public comments.

²⁰“Concentrated low-income areas” are 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 50 percent or more of the households earn incomes at less than 60 percent of the area median income (AMI), and are designated as Qualified Census Tracts in accordance with section 42 of the Internal Revenue Code. For more information, see the final SAFMR rule here: <https://www.huduser.gov/portal/datasets/fmr/fmr2016f/SAFMR-Final-Rule.pdf>

group includes PHAs in metropolitan areas that are just below the HUD threshold, specifically those that are within 90% of either of the first two criteria, but pass both the vacancy rate and PLI thresholds and contain more than 2,500 voucher holders. This results in 24 comparison metropolitan areas. A visual representation of the comparison group, as well as the distributions of all four criteria variables and a map of selected metropolitan areas, are found in online appendix C.

4.2 Sample

Small Area FMRs are attached to the ZIP Codes where voucher holders lease homes, not to the PHA that is administering the voucher.²¹ For this reason, we restrict our sample to households receiving vouchers from PHAs that had at least 80% of their voucher holders in one of the 23 metropolitan areas required to begin using Small Area FMRs in 2018 or the comparison metropolitan areas, using a cross section of voucher holders in 2018. We then further restrict the sample to the set of PHAs that had adequate data quality in the administrative database used to calculate success rates (online appendix D).

After applying both the geographic and data quality standards, our final sample consists of voucher recipients in 89 PHAs in 23 treated metropolitan areas²², and recipients in 109 PHAs in 24 comparison metropolitan areas that just missed the cut-off for being required to use Small Aea FMRs. These PHAs collectively issued between 25,000-41,000 new vouchers in each of the seven years from 2015 to 2021.

Table 1 shows that racial and ethnic composition, as well as family status, are very similar across treatment and comparison groups. As compared to households in the comparison group, a slightly smaller share of the Small Area FMR sample have a Black or Hispanic head of household, and a slightly larger share are female-headed households with children and have zero income. But overall, household characteristics are quite evenly balanced. Additionally, the two groups look fairly similar with respect to the characteristics of the neighborhoods where voucher recipients live when receiving search vouchers (Table 1). Voucher recipients in Small Area FMR metropolitan areas appear to originate in neighborhoods with somewhat lower Black and Hispanic population shares, and newer housing stocks. On the whole,

²¹In other words, if a voucher recipient receives a voucher in a PHA that operates mostly outside of one of the metropolitan areas mandated to use Small Area FMRs but leases up in a ZIP Code in one of those metropolitan areas, they are subject to Small Area FMRs.

²²We omit Dallas, TX, as a version of Small Area FMRs was already in place for two of the PHAs prior to the new Small Area FMR rule. We remove two demonstration PHAs that fall in either the treatment or comparison group metros: the Housing Authority of Cook County, as Chicago is a Small Area FMR metro, and City of Long Beach Housing Authority, as Los Angeles is in the comparison group. We also remove the Boston Housing Authority as the agency adopted a version of spatially varying rent subsidies during the sample time period.

however, differences are relatively small. This is important for our key outcomes, as past research shows that origin neighborhood attributes predict both success rates and search times (Ellen et al., 2024). Including metropolitan area fixed effects in our regressions helps to control for these baseline differences.

4.3 Empirical specification

We estimate a differences-in-differences regression model to isolate the effect of ZIP Code rent ceilings on our outcomes of interest. Small Area FMRs went into effect on April 1, 2018, but those issued a search voucher prior to this date were still subject to the new Small Area FMR rule if they leased up after April 1, 2018. Since most voucher holders (67%) who were issued a search voucher in the first three months of 2018 leased homes after April 1, we categorize all search events starting in 2018 as “post treatment.” We treat 2017 as an announcement year, since the PHAs learned at the end of 2016 that they were going to be required to adopt ZIP Code subsidies in the last quarter of 2017 (though the mandate was ultimately delayed until early 2018), and may have adjusted practices accordingly. As a result, we define the baseline, or pre-Small Area FMR period as 2016 and earlier. Our results hold if we include 2017 in the pre-period.

Our regression equation takes the following form:

$$Y_{itm} = \mathbf{X}'_{it}\beta + \delta \text{SAFMR}_m \times \text{AnticipatoryYear}_t + \tau \text{SAFMR}_m \times \text{Post}_t + \text{Year}_t \times \text{Region}_r + \text{MetroArea}_m + \varepsilon_{itm} \quad (1)$$

where Y represents our outcomes of interest (e.g., change in poverty rate percentiles between destination and origin census tract) for household i in year t in metro area m (in $Region\ r$), X' is a vector of individual/household controls, $Post$ is a dummy variable indicating that t is a post-treatment year, $SAFMR$ is a dummy indicating that the voucher holder receives their voucher from a PHA in a Small Area FMR metro area. Individual controls include the race and ethnicity of the household head, household composition, age of household head, disability status, citizenship status, and an indicator for whether the household was living in public housing the year prior to receiving their voucher. Equation 1 includes $Year$ by $Region_r$ fixed effects, which adjust for trends across time within the four Census regions, and $MetroArea_m$ fixed effects that control for any baseline differences across metro areas. For binary outcomes, we estimate linear probability models. Standard errors are clustered by PHA.

Additionally, we use an event study model to test for pre-trends and to show how the effect of Small Area FMRs evolves over time. In these models, we use one-year time period

dummies.

$$Y_{itm} = \mathbf{X}'_{it}\beta + SAFMR_m \times \sum_{j=2015}^{2021} \gamma_t \mathbb{I}(t-2016 = j) + Year_t \times Region_r + MetroArea_m + \varepsilon_{itm} \quad (2)$$

where j is an indicator variable for each year. We use 2016 as the reference year in the event study, and treat 2017 as an anticipatory year. Standard errors are clustered by PHA.

5 Results

5.1 Effects on locational and search outcomes

5.1.1 Locational outcomes

In online appendix E, we first show that there were no effects on the number of vouchers issued, the number of new voucher recipients admitted to the program, or the composition of voucher issuances²³ or admissions. Note, shifting to ZIP-code level subsidies did not come with any additional vouchers.

We then turn to examining effects on attributes of the neighborhoods where households use their vouchers. Figure 1 plots raw, uncontrolled differences between the rent ratios and poverty percentiles of origin and destination neighborhoods of voucher recipients who successfully lease homes with their vouchers. For the change in rent ratio (top left panel, Figure 1), the comparison group and treatment group track fairly closely in the two years prior to implementation). The two lines diverge sharply in 2018, with the change in rent ratio rising sharply for voucher recipients in Small Area FMR metros. Looking at the change in poverty percentiles (top right panel) in Figure 1, we see that the two groups again tracked fairly closely before implementation. After implementation, the Small Area FMR group sees a small decline in poverty rate change, suggesting new voucher recipients in these PHAs moved to relatively lower poverty neighborhoods as compared to the comparison group.

As additional context, Table 2 shows the average rent ratios and poverty percentiles for origin and destination neighborhoods in the treated and control PHAs, before and after the adoption of Small Area FMRs. Voucher holders in the control PHAs, on average, lease homes in ZIP Codes that have slightly lower rents relative to their origin neighborhoods, both before and after 2018. By contrast, while voucher holders from treatment PHAs also lease homes in ZIP Codes with lower rents on average than their origin neighborhoods prior

²³Even if SAFMRs led to changes in the composition of applicants or voucher issuances, changes would take a long time to materialize. Most households who receive vouchers wait for multiple years, and in practice, many waitlists are closed for long periods of time.

to the adoption of Small Area FMRs, after 2018, they settle in ZIP Codes with rents that are higher on average than those of their origin neighborhoods. Table 2 also shows that on average voucher holders do not see big gains in neighborhood environment when using their vouchers: they land in neighborhoods with slightly lower poverty rates, relative to the metro area poverty rate, than the ones where they start. But while the reductions in neighborhood poverty get smaller after 2018 for control group voucher holders, they grow larger over time for those in the treatment group. So by both of these measures, voucher holders in Small Area FMR PHAs experience greater improvements in neighborhood environments than their control group counterparts after the adoption of Small Area FMRs.

Moving to regression results, Table 3 shows results from the differences-in-differences models, where we find significant effects across most of our core locational outcomes. We find that the shift to ZIP Code-level rent subsidies resulted in significant increases in the change between origin and destination neighborhood rent ratios, and declines in the change between origin and destination poverty percentile. In other words, households in the treatment group were more likely to move to higher rent and/or lower poverty neighborhoods than where they originated, relative to the comparison group. Our effect sizes of just over 2 percentage points for rent ratio and 3 percentile points for poverty percentile represent substantial gains for voucher recipients in the treatment group, given that the average change between origin and destination neighborhoods was close to zero for both variables in the pre-treatment (See Table 2). Note that the moves to ZIP Codes with lower poverty percentiles on average translate to meaningful declines in neighborhood poverty rates. Households in the treatment group who moved to a lower poverty ZIP Code had an average origin poverty rate of 23%, but a destination poverty rate of 11%.²⁴

The next columns show coefficients from regressions of dichotomous outcomes capturing whether households move to neighborhoods that are more/less advantaged than the neighborhoods where they receive their voucher. We find that new voucher recipients in the treatment group were 6.7 percentage points more likely to move to a higher rent neighborhoods, and 6.0 percentage points more likely to move to a lower poverty neighborhood in the post period. These treatment effects both represent an 18% increase off the pre-treatment averages. While there were no significant declines in the probability of moving to a lower rent neighborhood, voucher recipients in the treatment were 3.6 percentage points (10%) less likely to move to a higher poverty neighborhood.

The last two columns show treatment effects using just the destination poverty percentile as the dependent variable, at both the ZIP Code and census tract level. We find significant

²⁴When we estimate our regressions using poverty rates, as opposed to percentiles, we see treatment effects of around 1.2 percentage points.

declines for both measures, though effects are smaller at the census tract level. The -0.015 decline in destination census tract poverty percentile translates to a roughly 1 percentage point decline in the poverty rate, or a decline of 4.8 percent; this effect size is slightly larger but consistent with the .97-.99 percentage point (3.7 percent) reduction in poverty exposure for new voucher recipients reported in (Eriksen et al., 2024), which uses a similar empirical strategy. This could indicate that some treated households are seeing smaller declines in their immediate neighborhood’s poverty rate, within larger ZIP Codes with lower poverty rates. However, we continue to rely on ZIP Codes for our baseline results since we cannot observe a voucher recipient’s census tract at the time they receive their voucher. As a result, we cannot construct measures that show the change between origin and destination census tract to observe upwardly (or downwardly) mobile moves.

Results from event study models demonstrate the lack of pre-trends and show how treatment effects evolved over the post-treatment time period. This is important both because we expect effects to grow over time as PHAs and households have more time to adopt to new payment standards, and because we find suggestive evidence of uneven compliance across PHAs in the first year after implementation. Panel A of Figure 2 shows the event study plot for the change in rent ratios and poverty rate percentile between origin and destination neighborhoods. For both variables, there are no observable pre-trends, but in the four years after the adoption of Small Area FMRs and in line with results from the difference-in difference models, we see significant effects which grow over time. For the rent ratio, we see that the coefficient for the change in the rent ratio increases significantly in the first year immediately after implementation, and increases again in 2019.²⁵ We also see statistically significant declines in neighborhood poverty percentile relative to the comparison group, which also grow after 2018.

By the fourth year of treatment (2021), on average, the difference between the destination and the origin rent ratio is 0.038 higher in Small Area FMR areas after implementation, relative to comparison areas. As for change in poverty rates, on average, new voucher recipients in Small Area FMR PHAs experienced a nearly 4 percentile point greater decline in neighborhood poverty rate percentile when using their voucher than new voucher recipients in the comparison group. To put these results into a broader policy context, we can compare the decline in poverty percentile to that from the MTO experiment. Quigley et al. (2008) show that on average, MTO led to about an 8 percentile point decline in the neighborhood poverty rate for the treatment group. Our treatment effect of 4 percentile points in 2021 is roughly half of this effect. This is a substantial effect given that voucher recipients started off in lower

²⁵Results are qualitatively very similar using the destination neighborhood’s rent ratio as the outcome variable. See Appendix D.

poverty origin neighborhoods than MTO participants, and that voucher recipients in Small Area FMR metros were not required to use their vouchers in low-poverty neighborhoods and nor were they systematically offered search counseling.

The left side of Panel B of Figure 2 shows similar patterns for dichotomous locational outcomes. The enactment of Small Area FMRs increased the likelihood that voucher holders move to higher rent and lower poverty ZIP Codes, both reflecting ‘upwardly mobile’ moves. By 2021, Small Area FMR households were over 10 percentage points more likely to move to a higher rent ZIP Code, and just under 10 percentage points more likely to move to a lower poverty ZIP Code. On the right side of the figure, we show that Small Area FMRs also helped reduce the prevalence of downwardly mobile moves, at least as measured by increases in neighborhood poverty. By 2021, voucher recipients in Small Area FMR metro areas were more than five percentage points less likely to move to a ZIP Code with a higher poverty rate than their ZIP Code of origin.

In online appendix F, we show results using several additional metrics of neighborhood opportunity. Using data from the ACS, we find that new voucher recipients are more likely to move to ZIP Codes with a higher share of adults with college degrees, higher median incomes, and higher employment rates. We also use the Opportunity Atlas metric of average income rank for low-children (?) which is measured at the census tract level rather than ZIP Code. We find no effect when looking at the destination census tract for successful households, though we are unable to compare this to the census tract of origin. In results not shown, we also see little impact on changes in neighborhood racial composition or the share of households with vouchers. Additionally, while we see positive locational outcomes for households that move ZIP Codes, we see little evidence of effects on the probability of moving ZIP Codes (online appendix G).

5.1.2 Success rates and search duration

Our analysis shows that using subsidy caps that vary across ZIP Codes, on average, has increased the share of voucher recipients who use their vouchers to move to higher-rent and lower-poverty neighborhoods. But a key question is whether that has come at the expense of other objectives, and in particular, a household’s ability to use their voucher to rent a home at all.

Figure 3 plots raw, uncontrolled success rates over time, or the share of voucher recipients who successfully lease homes with their voucher, as well as the median time it takes successful voucher recipients to do so. While success rates were higher and search times were longer in Small Area FMR metropolitan areas at baseline, the trends were mainly consistent between the treatment and control groups, both before and after the adoption of Small Area FMRs.

As for regressions, despite concerns that Small Area FMRs may reduce success rates or increase search costs, we find no significant impacts on either success rates or search times. Table 4 shows results from our core differences-in-differences models. While the post coefficient is negative in the success rate regression and positive for search time, neither reaches statistical significance.

The event study plots in Figure 4 confirm these results. There are no clear pre-trends (though search outcomes look more volatile from year to year than locational outcomes). None of the coefficients on the SAFMR*year interaction variables reach statistical significance.

5.1.3 Robustness

We conduct several additional robustness checks to confirm our findings with respect to both locational and search outcomes. First, in online appendix tables H1, H2, and H3, we show that our core locational and search results are not sensitive to the individual controls or region fixed effects that are used in our standard estimation strategy, or time-varying local economic conditions (as measured by county-level unemployment rates).

Second, we replicate all of our analyses using a version of the treatment group that is restricted to only metro areas that are as close to the selection thresholds as the comparison group (online appendix H). We find very similar results across all outcomes.

Third, we use two alternative comparison groups: an expanded comparison group that includes 40 metro areas within 80 percent of HUD’s selection criteria, and the group of 39 metro areas that was selected in the fall of 2023 to implement SAFMRs beginning in 2025.²⁶ Both of these groups have similar demographics and pre-trends to the Small Area FMR treatment group. Appendix Tables 14 and 15, we show raw trends and event studies and estimates for success rates using these alternative comparison groups show point estimates in the event studies for success rates that are again close to zero but now are generally positive (in contrast to point estimates in baseline regressions that were generally negative.²⁷).

Our standard models have confidence intervals that allow us to rule out any potential decline in success rates larger than 6 percentage points in our differences-in-differences models, and 7.5 percentage points across the post-period years in our event study models. Using our alternative comparison groups, we can rule out any potential effects larger than 5 percentage

²⁶These metros were selected using the same selection criteria as the original 23 metro areas, but with more updated data. While 41 metros were selected, only 39 can be included in the alternative comparison group, as two metros contain no PHAs that meet data quality standards.

²⁷These negative coefficients may be driven in part by an idiosyncratic increase in success rates in our comparison group. (It is worth noting that the standard comparison group seems to have experienced an increase in success rates in the post-treatment period, relative to a broader set of metros; see figure 14.)

points. By way of benchmarking, these magnitudes are smaller than differences in success rates between PHAs in rural and urban counties, and smaller than the decline in national success rates between 2020 and 2022 (Ellen et al., 2025).

Online appendix tables H5 and H6 show that our locational findings also remain robust to using these alternative comparison groups. Additionally, for our locational outcomes, we show that results are qualitatively similar when using all PHAs with 80% of their voucher holders living in SAFMR metro areas, regardless of whether the PHA passes our data quality standards for measuring success rates (online appendix tables H5 and H6).

Finally, as an additional robustness check on our leasing success models, we remove any voucher issuances that are part of a special program, such as the Family Unification Program (FUP) or Mainstream vouchers (MS5), and we find similar results for lease-up (online appendix table H4).

5.2 Heterogeneity in effects

5.2.1 Locational outcomes

As noted above, there are reasons to believe that certain sub-groups of voucher recipients may not benefit from Small Area FMRs because they face greater hurdles to moving to higher opportunity neighborhoods, even with higher rent subsidies. Figure 5 shows treatment effects for a pooled period from 2018-2021 from stratified models for different demographic groups, origin ZIP Code rent levels, and PHA service area rent levels. Across the board, pre-trends are flat (results not shown).

The figure summarizes several notable results. First, we find that results hold for families with children, and if anything, they appear to be somewhat larger, at least when considering changes in rent ratios. This is reassuring given the evidence that children benefit the most from moves to higher opportunity neighborhoods. We see even more striking differences when we divide the sample by the age of the head of the household. We see robust impacts for households with heads under 65 but smaller, insignificant impacts for seniors²⁸ who may face higher moving costs and have far less to gain from moving to higher-rent neighborhoods.²⁹

³⁰ Despite concerns that households of color might face higher costs in moving to higher rent

²⁸While we see a positive coefficient in the pooled differences-in-differences models, in the event study specification (not shown), we see no significant trends, and effects in 2020 and 2021 are very close to zero.

²⁹In the Small Area FMR demonstration, the final evaluation found that elderly voucher holders and those with disabilities were less likely to search in opportunity ZIP Codes because their current units were close to medical providers and other resources (Dastrup et al., 2018).

³⁰It's important to note that while we see strong locational outcomes for households with children and younger households, only households with two or more children and Hispanic households are significantly more likely to move ZIP Codes (online appendix figure G1) after implementation, indicating that for most

ZIP Codes, Figure 5 shows that our main location results also hold for Black and Hispanic households.

As for heterogeneity by origin neighborhood, we see modest differences. Point estimates for the change between origin and destination rent ratios are largest for those starting in low-rent neighborhoods. Coefficients are still positive for those starting in moderate or high rent neighborhoods, though insignificant; this is partially due to a smaller sample size and larger standard errors for these groups, as about half of voucher recipients originate in low-rent neighborhoods.³¹ The difference may also be driven in part by the fact that there are simply fewer destination neighborhoods that have higher rents than origin neighborhoods for households starting out in high-rent neighborhoods. Households originating from all three types of neighborhoods see declines in poverty percentiles relative to the comparison group, though coefficients only reach 10% significance for households who originate in low and high rent neighborhoods. Estimated impacts on poverty are largest for households originating in moderate rent ZIP Codes.

Next, we turn to heterogeneity along two different dimensions of PHA service areas. First, we examine impacts for PHAs that predominately serve low-rent ZIP Codes that experience a decline in payment standards. At these PHAs, it may be more difficult for voucher recipients to find homes in higher rent areas where payment standards rose. However, despite these concerns, in figure 5 we show that treatment effects for the group of PHAs that predominately serve low-rent neighborhoods are very similar to those at all other PHAs, for both change between origin and destination rents and poverty percentiles.

Second, we test if impacts are larger for PHAs that are more exposed to changes in payment standards because they serve areas with higher levels of dispersion in rents. At PHAs with relatively flat rents, adopting Small Area FMRs may have caused little change in payment standards across their service areas, while PHAs with high levels of rent dispersion may have seen more dramatic changes in neighborhood affordability. We define PHAs in the lowest quartile of rent dispersion as “low dosage” PHAs, and those in the highest quartile as “high dosage PHAs.” As expected, we find no neighborhood impacts in low-dosage PHAs that were less exposed to changes in payment standards, while effects are strong for PHAs with moderate or high levels of rent dispersion. Differences across groups are larger and more precisely measured for changes in poverty percentile.

Finally, we consider heterogeneity by metropolitan area. Appendix Figure 13 shows considerable variation in estimated treatment effects across metropolitan areas. The impact of the adoption of Small Area FMRs on the change in rent ratio between origin and desti-

subgroups, ZIP Code subsidies caused locational shifts through changing destination choices.

³¹Note that in event study results (not shown), trends are quite similar between the three groups.

nation neighborhoods ranges from positive 7 percentage points in Tampa, FL to negative 2 percentage points in Atlanta, GA. Similarly, the estimated treatment effect on the change between the origin and destination neighborhood poverty rate percentile ranges from negative 8 percentile points to positive 2 percentile points.

As for the drivers of this cross-metro variation, the coefficients on the interaction terms in Table 5 show that treatment effects on poverty rate percentile changes are smaller in areas with higher levels of racial segregation and older housing stocks, perhaps reflecting constraints on mobility. Importantly, we also see that impacts on poverty rate percentile changes are smaller (less negative) in metro areas in which the correlation between neighborhood rent and poverty rate is lower. In these areas, voucher recipients may be more successful in getting to higher rent neighborhoods (than voucher recipients in comparison metros), but these neighborhoods may not have lower poverty rates. For example, in the Pittsburgh metro area, which has the lowest correlation between the rent ratio and the poverty rate percentile among the 23 metro areas in our treatment sample, the adoption of Small Area FMRs actually led voucher recipients to higher poverty neighborhoods on average. Similarly, in Monmouth-Ocean, NJ, the coefficients on SAFMR in both the rent ratio and poverty rate percentile regressions are positive; again, the correlation between neighborhood rents and poverty rates are low in this metro area.

5.2.2 Success rates and search duration

As noted above, advocates and PHA staff have voiced distributional concerns that the adoption of Small Area FMRs will increase search costs and reduce success rates for voucher recipients from low-rent neighborhoods. But our results are reassuring, we see no significant declines in successful voucher use for households at any origin rent level (Figure 6). Despite concerns that Small Area FMRs may make it more difficult for voucher recipients in lower rent areas to lease homes, or may require them to search for longer to find units, our results indicate that SAFMRs have no significant impact on leasing success or search times in the four years after implementation, even for those starting in low-rent ZIP Codes.

Similarly, we see no evidence that SAFMRs lead to worse lease-up or search time outcomes for households receiving vouchers from PHAs predominantly serving low-rent areas. In terms of search times, voucher holders from PHAs that predominantly serve low-rent ZIP Codes actually see a decline in search time after Small Area FMR adoption. Treatment dosage doesn't seem to matter for search success or duration either. Across low, moderate and high dosage PHAs, there are no significant effects on successful voucher use or search time; while standard errors can be large, coefficients are close to zero across the three groups.

When we look at variation by household demographics, we see no significant differences

by the age of the household head or number of household members, which is our proxy for the presence of children.³² We find some evidence that success rates fell for Hispanic households (Figure 6). We also see some evidence of increased search time for Hispanic and white households.

As a robustness check, we replicate our heterogeneity analyses using the two alternative comparison groups described above: an expanded comparison group using lower thresholds than HUD used for its selection criteria, and the group of metro areas selected to use ZIP Code-level subsidies beginning in 2025. While our locational results hold for each sub-group, the negative effect on successful voucher use for Hispanic households becomes insignificant when we use alternative comparison groups. Indeed, we do not observe negative impacts on successful voucher use for any sub-groups when using either of these alternative comparison groups (online appendix J presents results).

5.3 Costs to housing authorities

One concern about Small Area FMRs is that the increase in ceiling rents in higher rent neighborhoods could raise the subsidy cost for PHAs, and result in fewer households being served. To test this, we examine the amount of rent paid by the PHA for every new voucher holder, using our standard event study approach (equation 2). As expected, Panel B shows that after the adoption of Small Area FMRs, PHA housing subsidy payments increased for recipients leasing homes in higher rent ZIP Codes and decreased for those leasing in lower rent ZIP Codes (Figure 7). But Panel A shows that these changes appear to offset each other in terms of overall PHA subsidy costs, as there is no significant change in the PHA subsidy costs for Small Area FMR PHAs on average after implementation, relative to the control PHAs. (While it is encouraging that Small Area FMRs were on net cost neutral for new recipients, shifting to ZIP Code rent subsidies may not have been cost-neutral for existing voucher holders during this time frame given that HUD exempted sitting voucher recipients from the new rental subsidy framework in the short-run.)³³

³²Issuance data do not contain information on the presence of children in the household, so we cannot observe the exact number of children in households that do not succeed in using their vouchers. But among households who successfully lease up, 70% of two person households and more than 95% of households with at least 3 members contain at least one minor child.

³³Specifically, existing voucher holders who don't move could be held harmless, in some cases for several years.

5.4 Adjustment on other margins

The lack of impacts on success rates and subsidy costs seems to suggest that the increase in moves to higher rent and lower poverty neighborhoods that Small Area FMRs produce comes with no trade-offs. But there may be trade-offs on different margins, overall or for some subgroups. For example, the decline in subsidy caps experienced in lower rent neighborhoods may mean that new voucher recipients leasing in low-rent neighborhoods lease smaller, lower-quality homes or pay higher out-of pocket costs than new recipients leasing homes in such neighborhoods did under uniform rent subsidies.

To test for other impacts, we examine tenant contributions to rent and rent-to-income ratios for households who were successful in using their vouchers. In figure 8, we show that there were no statistically significant increases in tenant rent contributions, even for households who lease-up in neighborhoods where payment standards would have declined. Figure 9, Panel A, shows that after ZIP Code level subsidies were implemented, there was also no significant increases in rent-to-income ratios in aggregate. When broken out by destination ZIP Code rent (Panel B), we do see differences between subgroups; households who leased up in low-rent ZIP Codes had statistically significant higher rent-to-income ratios after adoption of Small Area FMRs. This reflects an increase in new recipient households renting homes with rents above the payment standard in these ZIP Codes, increasing their out-of-pocket costs for rent. Specifically, rent-to-income ratios of households who lease in low-rent ZIP Codes are around 1 percentage point higher after the adoption of Small Area FMRs, which equates to a nearly 3 percent increase off of the pre-treatment average rent-to-income ratio of 33.4 percent. There is a mirroring decline rent-to-income ratios for new recipients who lease homes in high-rent neighborhoods, so no overall increase in rent burdens. These effects are significant despite no statistically significant changes in tenant rent contributions as there were corresponding (though also insignificant) changes in adjusted income across this time period, which is shown in online appendix table K1.

Another area where households may make adjustments is in the size of the leased home. We find that voucher recipients in Small Area FMR metros move into homes with fewer bedrooms when they lease homes in low-rent ZIP Codes. Specifically, Figure 10 shows that after adoption of Small Area FMRs, new voucher recipients leasing homes in low-rent ZIP Codes were less likely to use their subsidies to rent homes that have more bedrooms than the number for which their household qualifies. Here we see no mirroring change for those leasing in high-rent ZIP Codes, and there is no significant change in aggregate.

Figures 9 and 10 provide evidence that Small Area FMRs induce other significant changes in housing size and costs differentially between low-rent and high-rent neighborhoods (though not in aggregate). To probe potential changes in the housing bundle further, we examine

the gross rents of units occupied by new voucher holders. Changes in gross rents may reflect changes in the unit size or quality, changes in the neighborhood quality, or also changes in rents charged to voucher households. The top panel of Figure 12 shows that in the aggregate, there was no change in the gross rent charged for units with new voucher holders (the blue points). The next two panels show that the total rents charged (the blue points) for units that voucher recipients leased declined in low-rent neighborhoods where payment standards declined, and increased in high rent neighborhoods. By 2021, gross rents charged for units occupied by voucher holders declined in low-rent neighborhoods by about \$170, a substantial decrease compared to the average gross rent in that year of \$1,300.

A key question is whether the decline in rents charged for voucher units in low-rent ZIP Codes (Figure 12, Panel B) hold up when controlling for unit quality. In other words, are declines driven by landlords lowering the rents they charge to match new payment standards or are the declines due to adjustments by households who choose to rent smaller homes, lower quality homes, or homes in lower-rent neighborhoods within ZIP Codes? To decompose these different mechanisms, we first control for the number of bedrooms in the home (orange points) and see a smaller, though still large and significant decline in gross rents, indicating that voucher recipients renting smaller units explains a portion of the decline in charged rents.

When adding controls for building size, building age, and destination census tract fixed effects, the coefficients are unchanged, indicating that voucher recipients were not simply moving to older buildings or cheaper census tracts within low-rent ZIP Codes. Finally, we add in building level fixed effects, to test whether landlords are lowering rents for the same units in response to the change in payment standards. The coefficient falls to zero in 2018, but then grows more negative over time as landlords likely adjust to new payment standards.³⁴ Although we have limited measures of building quality, these results suggest that the decline in rents charged to voucher holders in low-rent neighborhood comes from a combination of voucher recipients renting smaller units and landlords adjusting rents, with roughly a third of the decline in rents driven by landlords lowering rents, though estimates are not precise.

Similarly, we see increases in gross rents in high-rent neighborhoods. Using the same set of models, we find that about one third of the increase in gross rents can be attributed to landlords raising rents for units in the very same buildings.

We also find evidence of tenant adjustment on another margin: movement out of service areas in PHAs that mainly serve low-rent ZIP Codes experiencing declines in FMRs. To test for this, we estimate similar regression models as above, but change the outcome

³⁴These estimates rely on buildings that house multiple new voucher recipients across our sample time period; roughly one third of new voucher recipients lease up into these buildings.

variable to whether a new voucher recipient leases a home outside the service area of their originating PHA (Figure 11). We see that the implementation of ZIP Code FMRs leads to a significant increase in such out-of-service area lease ups relative to the control group in the years following the introduction of Small Area FMRs for voucher holders from PHAs that predominantly serve low-rent ZIP Codes.³⁵

6 Conclusion

We find evidence that better aligning subsidies with ZIP Code rents led to improvements in neighborhood outcomes for new voucher recipients. The shift from uniform to ZIP Code subsidy pricing increased the share of new voucher holders moving to neighborhoods with higher rents and lower poverty rate percentiles as compared to their origin neighborhoods. The impacts generally grow larger in the subsequent years after Small Area FMR adoption, and are largest in PHAs with higher rent dispersion, or in areas where uniform rent subsidies were further from neighborhood market rents. Importantly, at least in the first four years of implementation, the neighborhood improvements experienced by new voucher recipients did not come at the expense of overall voucher success rates and did not increase overall subsidy costs for PHAs.

Both our locational effects and the lack of effects on successful voucher use hold for critical sub-groups, including new voucher holders originating in low-rent ZIP Codes and those receiving vouchers from PHAs that disproportionately serve low-rent neighborhoods. The only households that don't see locational gains after the adoption of Small Area FMRs are households headed by older adults, though this may not be so concerning since they have less to gain from moving to higher rent areas. The more muted gains in metropolitan areas with older housing stocks and characterized by high levels of racial segregation is more concerning, as is the reminder that rent levels don't always correlate highly with poverty rates. It could be useful for PHAs to consider other measures of a neighborhood beyond rent when determining their rent payment ceilings. As for success rates, the only sub-group for which we see evidence of declines in lease-up rates is Hispanic voucher recipients (though this finding is not robust to alternative comparison groups).

We did find some distributional impacts along other margins of adjustment. Specifically, under ZIP Code rent subsidies, new recipients leasing homes in low-rent neighborhoods paid more of their income towards rent and leased smaller homes as compared to new recipients in these neighborhoods under uniform payment standards. Over time, rents charged to voucher

³⁵Out-of-service-area lease ups increase significantly when port-outs (when vouchers switch PHAs who administer the voucher) are removed, so results are not driven by port-outs.

holders also declined in these neighborhoods, suggesting some adjustment by landlords. Small Area FMRs led to similarly sized decreases in rent-to-income ratios for households leasing in high-rent neighborhoods, hence altering the distribution of rent burdens but not changing overall levels. We also find that Small Area FMRs led more voucher recipients from PHAs serving low-rent areas to use their vouchers outside of their original PHA's service area. This could impose added costs on these households, as they need to search more broadly for affordable homes; or this could demonstrate a greater ability to reach more desirable neighborhoods with new subsidy levels. But overall, at least through the first four years of implementation, Small Area FMRs appear to have generated gains to neighborhood opportunity without a major trade-off in the form of declining success rates or increased costs to the government. Future work should explore longer-term impacts.

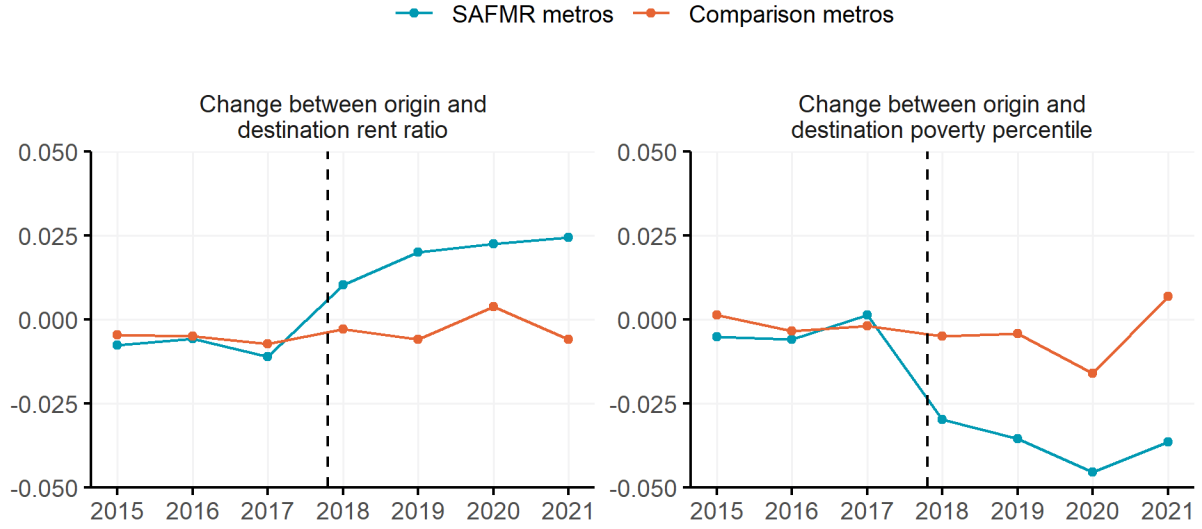
Tables and Figures

Table 1: Balance between SAFMR and comparison group

Variable	Treatment group	Comparison group	P value of difference
Individual variables			
Black head of household	0.613	0.624	0.87
Hispanic head of household	0.108	0.118	0.72
White head of household	0.240	0.230	0.83
Female head of household	0.764	0.739	0.51
Female headed with kids	0.531	0.491	0.30
Single	0.393	0.446	0.14
Disabled head of household	0.277	0.296	0.49
Noncitizen	0.023	0.025	0.76
Adjusted income = 0	0.804	0.785	0.83
Origin ZCTA variables			
Black share	0.297	0.311	0.80
Hispanic share	0.203	0.253	0.30
Poverty percentile	0.728	0.722	0.79
Share of housing stock built before 1940	0.142	0.178	0.42
Vacancy rate	0.061	0.059	0.77
Rent ratio	0.960	0.968	0.53
Voucher household share	37.9	43.7	0.20
Observations (all years)	73,930	147,797	

Note: Includes only observations from the pre-treatment period (searches that began between 2015 and 2017). Standard errors are clustered by PHA.

Figure 1: Raw change between origin and destination ZCTAs over time, uncontrolled



Note: Change between origin and destination outcomes are calculated as the destination value minus the origin value.

Table 2: Origin and destination rent ratio and poverty percentile by treatment status and time period

Group	Time period	Origin mean	Destination mean	Change between origin and destination	Destination ZIP is lower than origin	Destination ZIP is higher than origin
Rent ratio						
Treatment	Pre (2015-2017)	0.955	0.948	-0.008	0.321	0.305
Treatment	Post (2018-2021)	0.970	0.989	0.019	0.277	0.369
Comparison	Pre (2015-2017)	0.965	0.960	-0.005	0.342	0.335
Comparison	Post (2018-2021)	0.994	0.990	-0.003	0.313	0.335
All observations		0.974	0.974	0.000	0.316	0.336
Poverty percentile						
Treatment	Pre (2015-2017)	0.732	0.728	-0.004	0.341	0.308
Treatment	Post (2018-2021)	0.747	0.711	-0.037	0.398	0.277
Comparison	Pre (2015-2017)	0.728	0.727	-0.001	0.371	0.332
Comparison	Post (2018-2021)	0.728	0.724	-0.004	0.371	0.344
All observations		0.733	0.723	-0.009	0.371	0.321

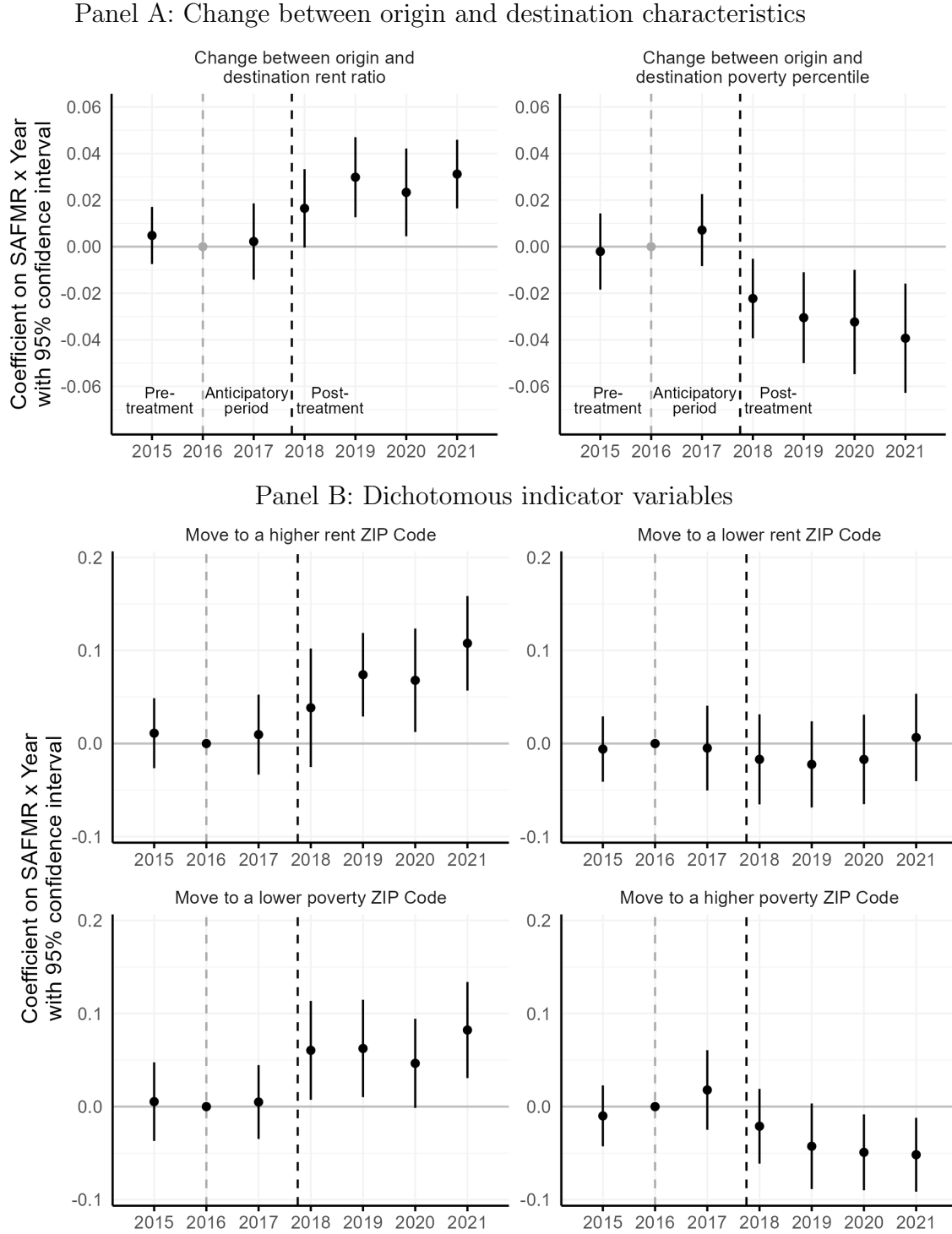
Note: Results are qualitatively similar when we remove 2017 from the pre-treatment period.

Table 3: Differences-in-differences table for locational outcomes

	Change between origin and destination		Upwardly mobile move indicators		Downwardly mobile move indicators		Destination poverty percentile	
	Rent ratio	Poverty percentile	Move to higher rent	Move to lower poverty	Move to lower rent	Move to higher poverty	ZCTA	Census tract
SAFMR x Anticipatory year	0.000 (0.007)	0.008 (0.006)	0.004 (0.020)	0.002 (0.018)	-0.002 (0.019)	0.023 (0.018)	-0.003 (0.008)	0.003 (0.009)
SAFMR x Post	0.023*** (0.006)	-0.030*** (0.009)	0.067** (0.020)	0.060** (0.020)	-0.010 (0.016)	-0.036* (0.014)	-0.025** (0.008)	-0.015* (0.008)
Observations	141,738	143,759	141,738	145,126	141,738	145,126	144,859	141,369
Adjusted R ²	0.025	0.019	0.037	0.041	0.028	0.023	0.166	0.095
Pre-treatment average	-0.006	-0.002	0.360	0.324	0.323	0.334	0.728	0.710
Year x Region fixed effects	X	X	X	X	X	X	X	X
Metro area fixed effects	X	X	X	X	X	X	X	X
Individual controls	X	X	X	X	X	X	X	X

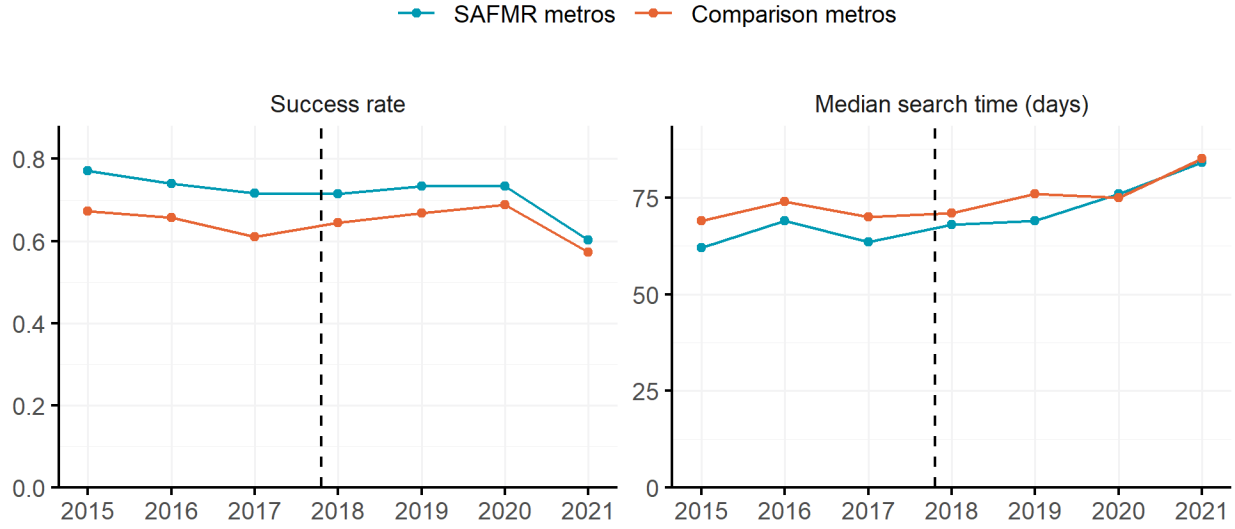
Note: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The table shows the results from differences-in-difference models, following equation 1. The sample includes new voucher recipients who were successful in using their voucher. Standard errors are clustered by PHA. 2017 is treated as an anticipatory year; results are qualitatively similar when 2017 is included in the pre-treatment period.

Figure 2: Event study plots for change between origin and destination characteristics



Note: Change between origin and destination outcomes are calculated as the destination ZIP Code value minus the origin ZIP Code value. The dependent variables in Panel B are dichotomous indicators for the destination rent ratio (poverty percentile) being lower (higher) than origin. Models include individual controls, year x region fixed effects, and metro area fixed effects. Standard errors are clustered by PHA.

Figure 3: Raw search outcomes over time, uncontrolled



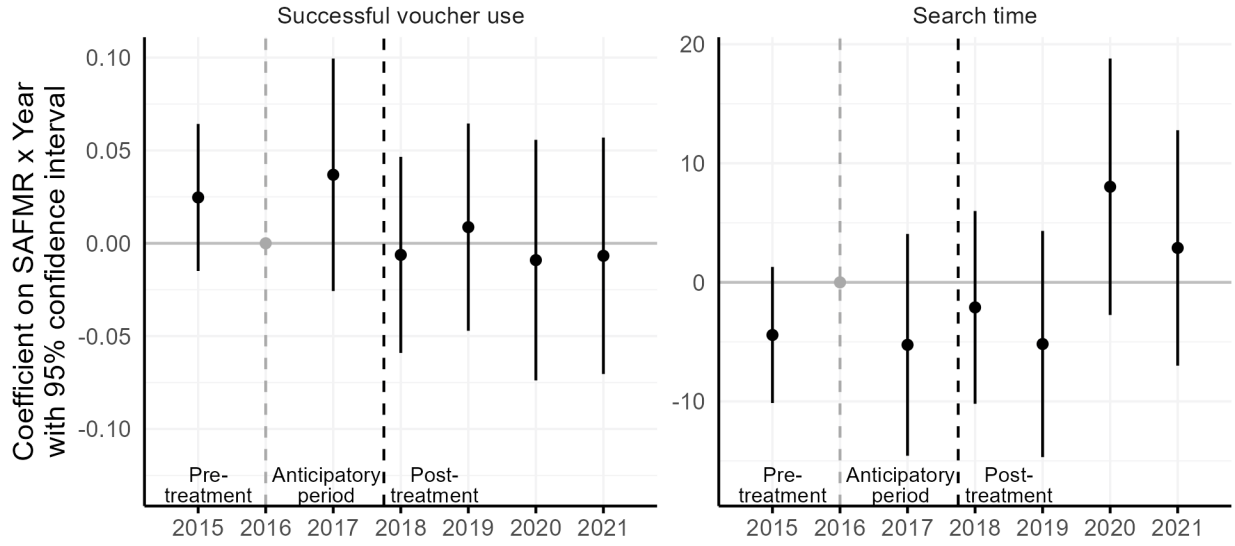
Note: Success rate is the share of searches that successfully use their voucher within 1 year of issuance. Search time is the elapsed time between the issuance of the voucher and successful voucher use, for households that are successful. Standard errors are clustered by PHA.

Table 4: Differences-in-differences regressions for search outcomes

	Successful voucher use	Search time (days)
SAFMR x Anticipatory year	0.024 (0.028)	-2.887 (4.324)
SAFMR x Post	-0.015 (0.022)	2.849 (3.910)
Observations	221,727	148,402
Adjusted R ²	0.051	0.098
Pre-treatment average	0.68	80.2
Year x Region fixed effects	X	X
Metro area fixed effects	X	X
Individual controls	X	X

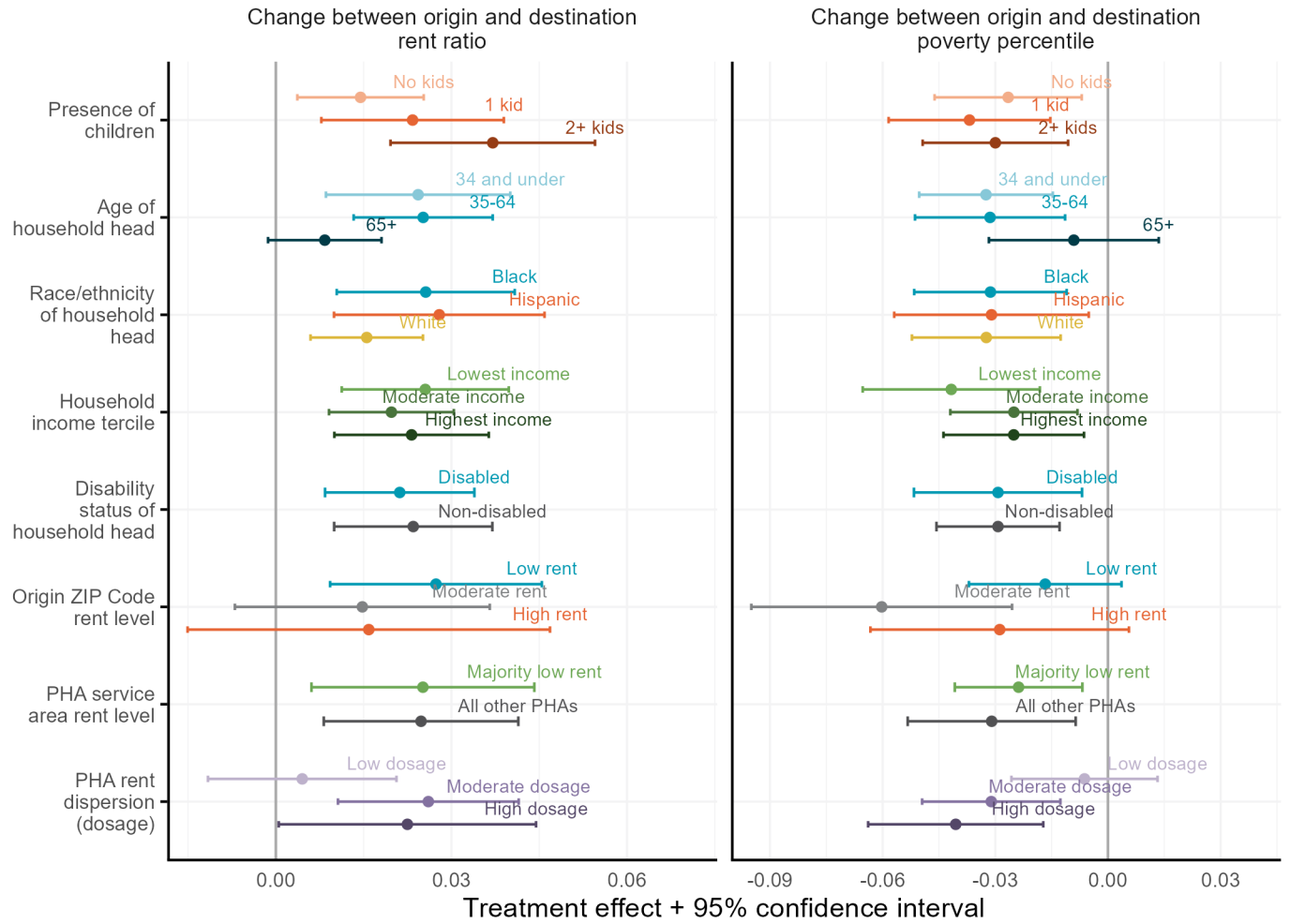
Note: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The table shows the results from differences-in-difference models, following equation 1. The dependent variable in the first column is an indicator for the voucher recipient successfully using their voucher within 1 year of issuance; the sample is all new voucher recipients. The dependent variable in the second column is the number of days between voucher issuance and successful lease-up; the sample is only new voucher recipients who are successful in using their vouchers. Models include individual controls, year x region fixed effects, and metro area fixed effects. Standard errors are clustered by PHA.

Figure 4: Event study plots for search outcomes



Note: Graphs depict coefficients from an event study model that follows equation 2. The dependent variable on the left panel is an indicator for the voucher recipient successfully using their voucher within 1 year of issuance. The dependent variable on the right is the number of days between voucher issuance and successful lease-up, for households who are successful. Models include individual controls, year x region fixed effects, and metro area fixed effects. Standard errors are clustered by PHA.

Figure 5: Heterogeneity in locational outcomes, 2018-2021



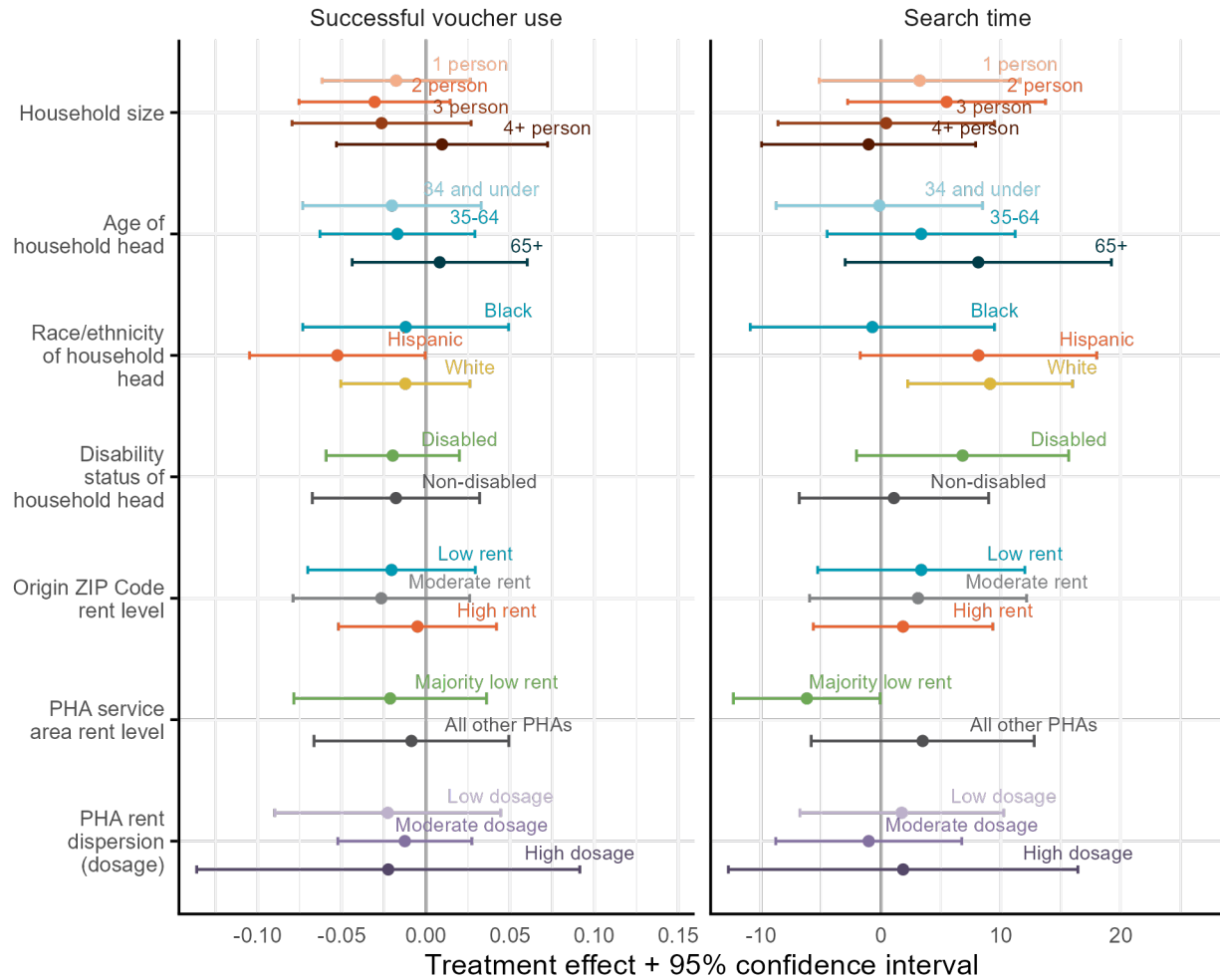
Note: The estimates shown above are treatment effects for the full post-period (2018-2021) from stratified differences-in-differences models, following equation 1. Models include individual controls, year x region fixed effects, and metro area fixed effects. Standard errors are clustered by PHA.

Table 5: Differences-in-differences regressions with interaction terms for metro area variables

	Change in rent ratio		Change in poverty percentile		
	(1)	(2)	(3)	(4)	(5)
SAFMR x Anticipatory year	0.000 (0.007)	0.000 (0.007)	0.008 (0.006)	0.009 (0.006)	0.009 (0.006)
SAFMR x Post	0.057*	0.025**	-0.090*	- 0.041***	0.017 (0.023)
SAFMR x Post x Black-white dissimilarity	(0.028) -0.063 (0.051)	(0.008)	(0.036) 0.111+ (0.059)	(0.012)	
SAFMR x Post x Share of housing stock built before 1940		-0.032 (0.058)		0.156* (0.064)	
SAFMR x Post x Rent poverty correlation					-0.077+ (0.041)
Observations	141,492	141,492	143,546	143,546	143,546
Adjusted R ²	0.025	0.025	0.019	0.019	0.019
Year x Region fixed effects	X	X	X	X	X
Metro area fixed effects	X	X	X	X	X
Individual controls	X	X	X	X	X
Simulated treatment effects					
at 10th percentile	-	-	-0.042	-0.038	-0.010
at average value	-	-	-0.027	-0.025	-0.028
at 90th percentile	-	-	-0.011	-0.007	-0.038

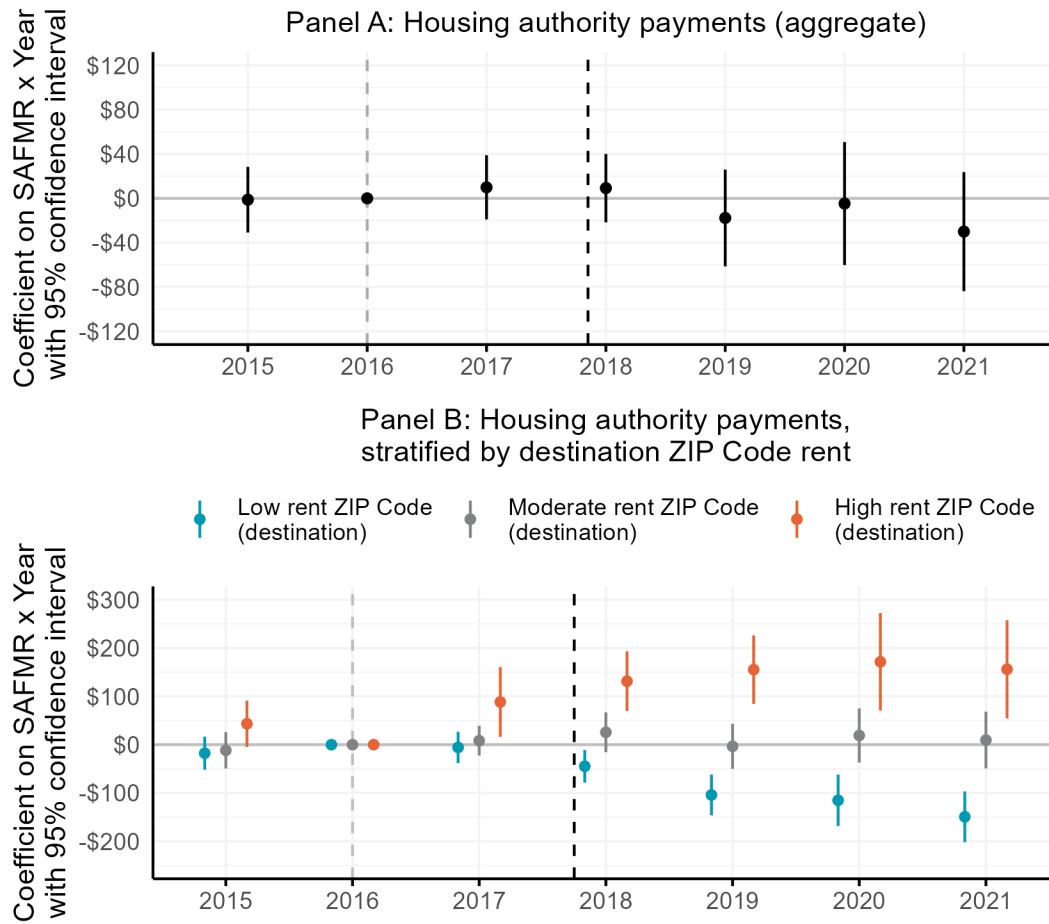
Note: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Results shown are coefficients for differences-in-differences models that follow equation 1, with the addition of interaction terms with continuous variables at the metro area level. The dependent variable for the first two columns is the change between origin and destination rent ratio; in the last three columns, the dependent variable is the change between origin and destination poverty percentile. Correlation between rent and poverty rate is calculated at the metro level, using ZIP Codes where there are voucher holders. We use the absolute value of the correlation coefficient. Models include individual controls, year x region fixed effects, and metro area fixed effects. Simulated treatment effects show the estimated effects at the 10th percentile, average, and 90th percentile of the given continuous variable interaction term; for example, in metro areas at the 10th percentile of black-white dissimilarity, we predict a stronger treatment effect of -0.042 poverty percentiles. Standard errors are clustered by PHA.

Figure 6: Heterogeneity in search outcomes, 2018-2021



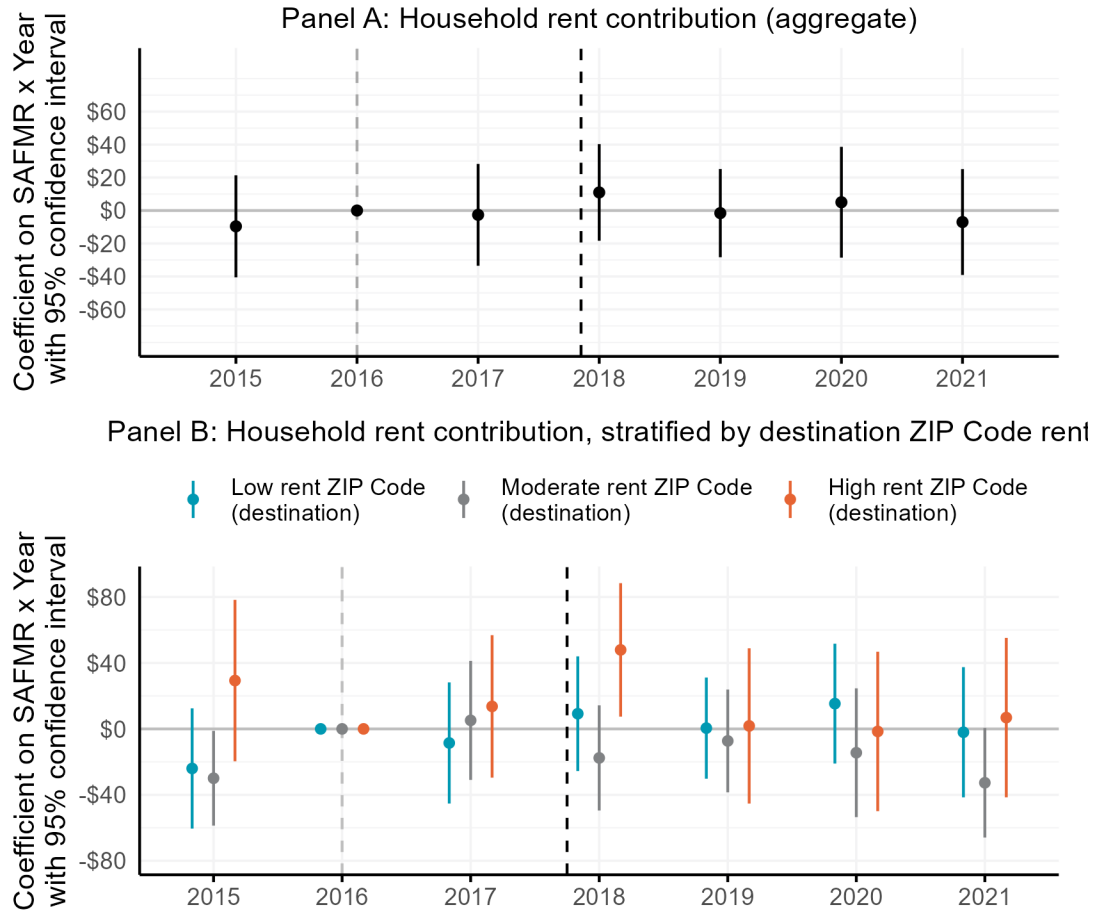
Note: The estimates shown above are treatment effects for the full post-period (2018-2021) from stratified differences-in-differences models. The dependent variable in the left panel is an indicator for the voucher recipient successfully using their voucher within 1 year of issuance; the sample is all new voucher recipients. The dependent variable in the right panel column is the number of days between voucher issuance and successful lease-up; the sample is only new voucher recipients who are successful in using their vouchers. Models include individual controls for all other attributes, year x region fixed effects, and metro area fixed effects. Standard errors are clustered by PHA.

Figure 7: Event study plot for housing authority payments (HAP)



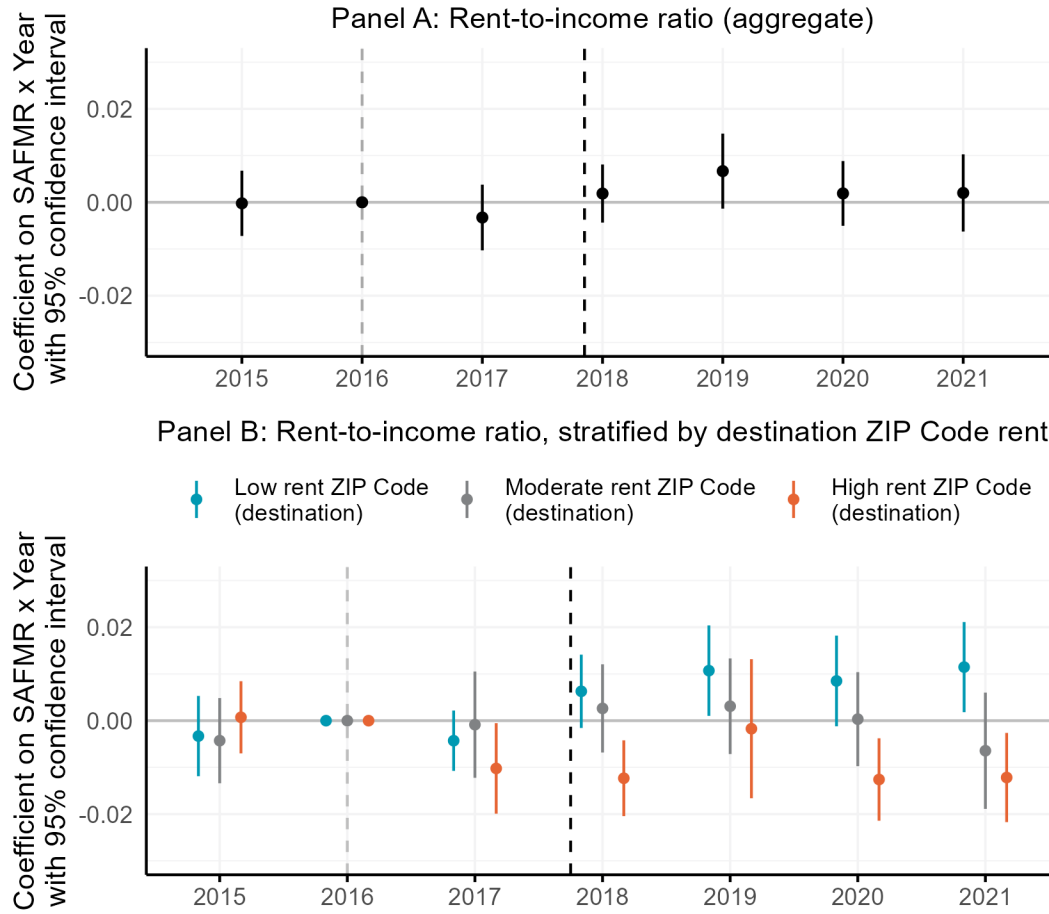
Note: Dependent variable is the housing authority portion of the gross rent, in nominal dollars. In Panel B, each set of points represents coefficients from separate stratified models. Models include individual controls, year x region fixed effects, and metro area fixed effects. Standard errors are clustered by PHA.

Figure 8: Event study plot for household rent contributions



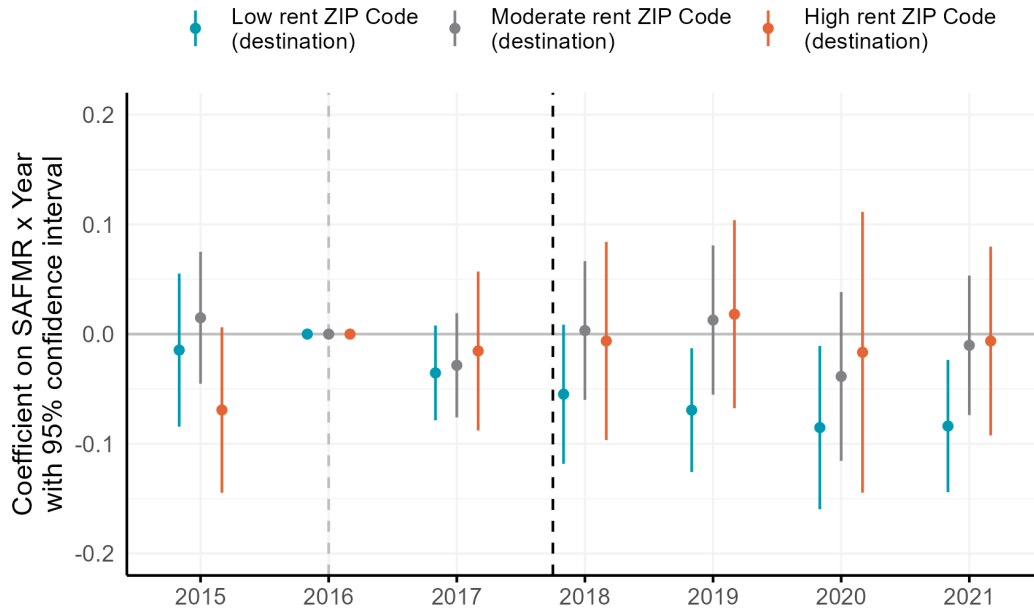
Note: The dependent variable in all models is the tenant portion of the gross rent, in nominal dollars. The sample for each model includes only successful searches where tenant rent contribution is directly observed on the day that the household enters the program. In Panel B, each set of points represents coefficients from separate stratified models. Models include individual controls, year x region fixed effects, and metro area fixed effects. Standard errors are clustered by PHA.

Figure 9: Event study plot for rent-to-income ratio



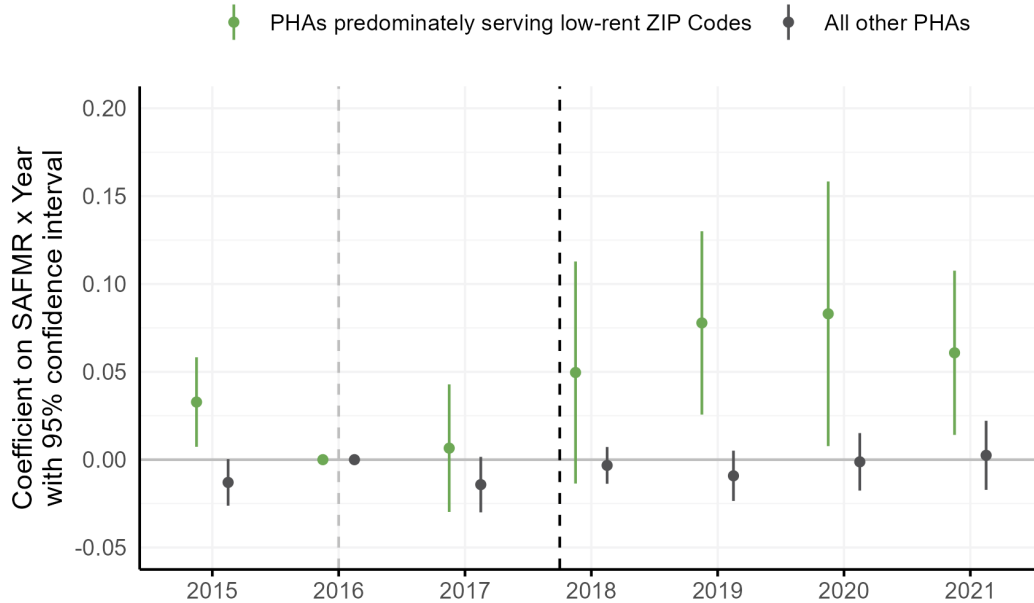
Note: The dependent variable in all models is ratio of the tenant's rent contribution to their adjusted monthly income. The sample for each model includes only successful searches where tenant rent contribution and adjusted income are directly observed on the day that the household enters the program. In Panel B, each set of points represents coefficients from separate stratified models. Models include individual controls, year x region fixed effects, and metro area fixed effects. Standard errors are clustered by PHA.

Figure 10: Event study plots for indicator for leasing up into a larger unit than qualified



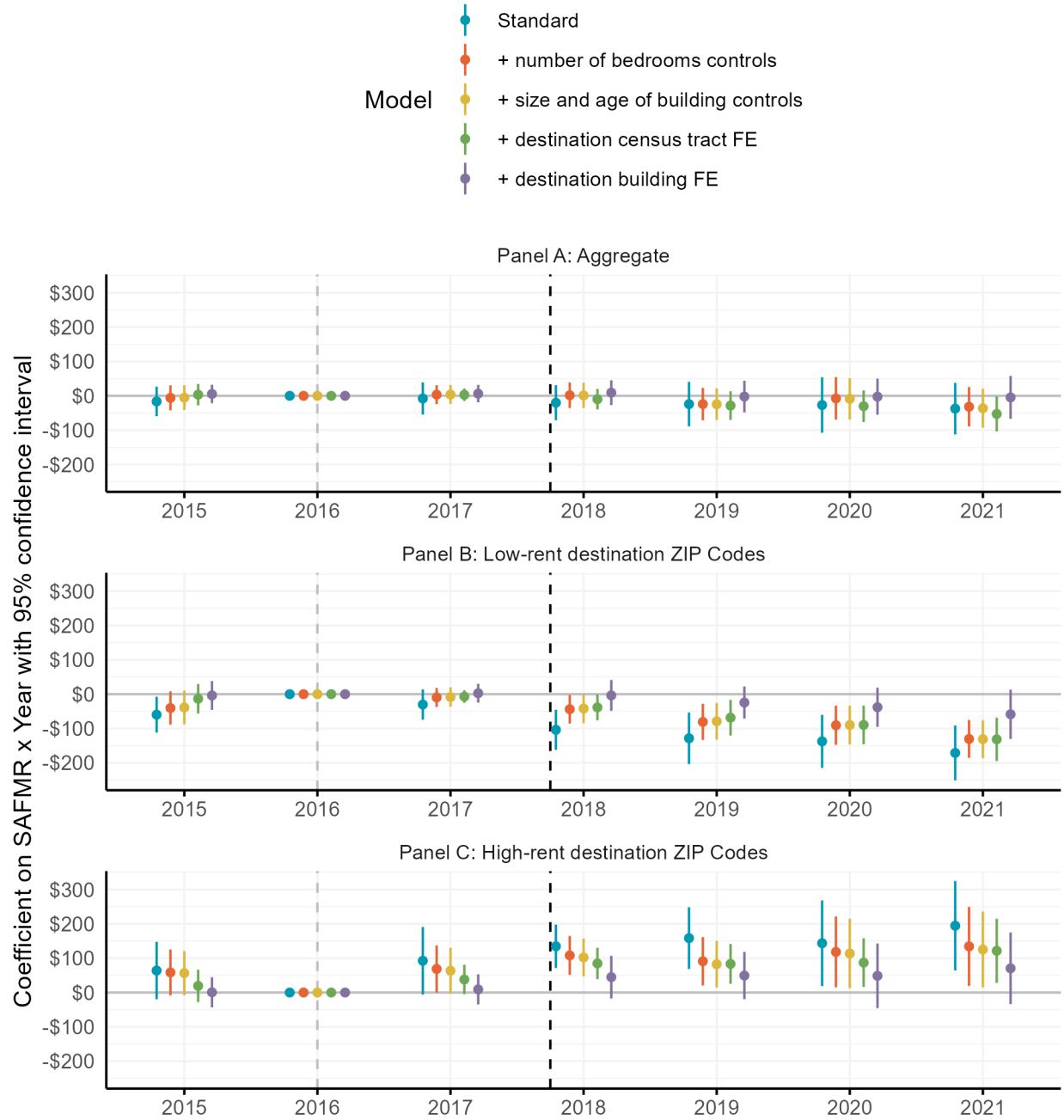
Note: The plot shows the event study where the dependent variable is an indicator for the actual bedroom size being larger than the qualified bedroom size for the household. Each set of point estimates are from separate stratified models. Models include individual controls, year x region fixed effects, and metro area fixed effects. Standard errors are clustered by PHA.

Figure 11: Event study plots for leasing up outside of PHA's service area, stratified by PHAs who disproportionately serve low-rent ZIP Codes



Note: The dependent variable is a binary indicator for whether the destination ZIP Code lies outside the origin PHA's measured service area. Each set of point estimates are from separate stratified models. PHAs who disproportionately serve low-rent ZIP Codes are defined as PHAs in the top tercile of the share of units where the Small Area FMR for a ZIP Code is at least 5% below the Metro Area FMR. Models include individual controls, year x region fixed effects, and metro area fixed effects. Standard errors are clustered by PHA.

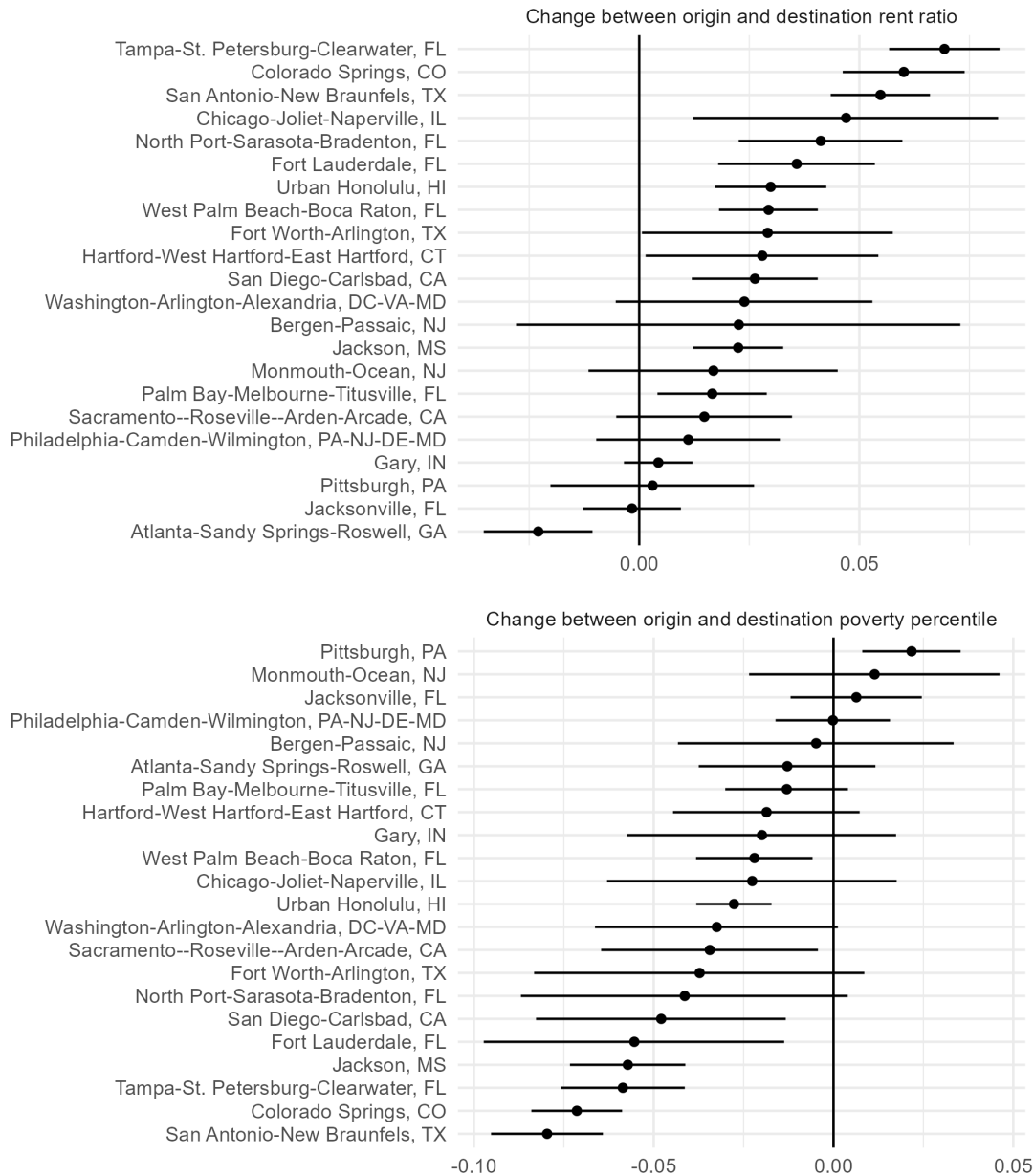
Figure 12: Event study plot for gross rent



Note: The dependent variable in all models is the gross rent of the housing unit, in nominal dollars. The points in each plot represent coefficients from models with different control variables and fixed effects. The standard model includes only year x region fixed effects and metro area fixed effects. The second model adds controls for number of bedrooms. The third adds additional controls for the structure type and the year the building was built. The fourth adds destination census tract fixed effects, while the fifth adds building fixed effects. In all models, standard errors are clustered by PHA.

Appendix

Figure 13: Treatment effects by metro area



Note: The plotted points are the interaction terms for metro area dummies; each metro is being compared to the full comparison group. We exclude Charlotte, NC due to a small sample size, but note that effects were positive for rent ratio and negative for poverty percentile, consistent with aggregate effects. Models include individual controls, year x region fixed effects, and FMR area fixed effects. Standard errors are clustered by PHA.

The following charts use different comparison groups to evaluate the effect of SAFMRs on success rates. The standard comparison group contains 24 metro areas that are within 90% of HUD's selection criteria (see online appendix D for more information on the selection criteria). The expanded group contains 40 metros that are within 80% of HUD's selection criteria. The SAFMR 2025 group contains 39 metro areas of the 41 that were selected to implement SAFMRs beginning in 2025; these metros were selected using the same selection criteria, but more updated data.³⁶

Figure 14: Raw trends in success rates over time, with different comparison groups

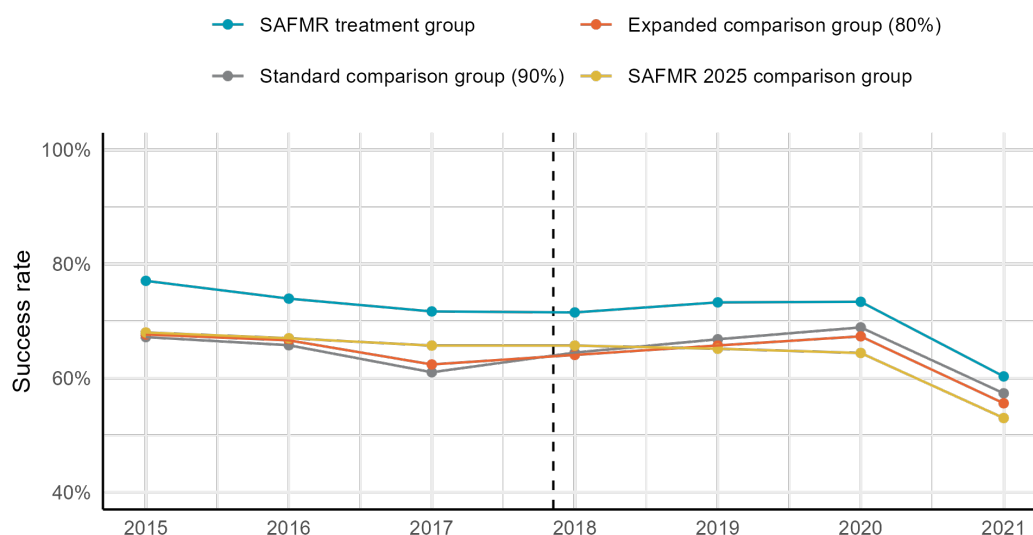
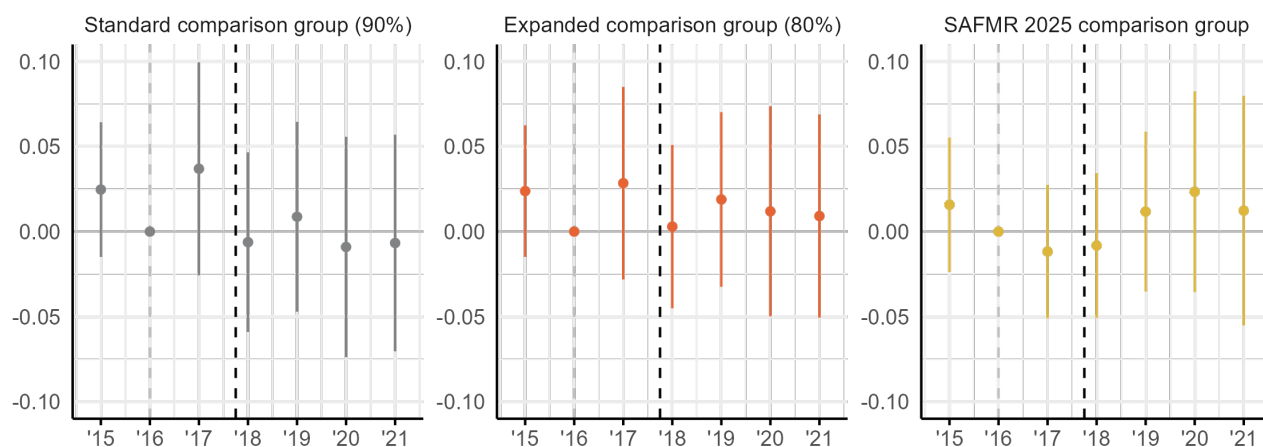


Figure 15: Event studies for successful voucher use, using different comparison groups



Note: The dependent variable in the event studies is an indicator for a household successfully using their voucher within 1 year of issuance. Models include year x region fixed effects, FMR area fixed effects, and individual controls. Standard errors are clustered by PHA.

³⁶Two metros are excluded as they have no PHAs that meet data quality standards across all years of our sample period.

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