Improving Access to Opportunity: Housing Vouchers and Residential Equilibrium*

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Abstract

This paper studies how policies that improve low-income households' access to high-opportunity neighborhoods at scale reshape residential equilibrium and welfare. I analyze Small Area Fair Market Rents (SAFMR), a redesign of the rental voucher program that increases subsidy caps in high-rent neighborhoods while lowering them elsewhere, inducing substantial relocation of subsidized households from low- to high-rent areas. This demand shift polarized the rental market: rents rose in high-rent neighborhoods and fell in low-rent neighborhoods. At the same time, it fostered a more integrated spatial equilibrium, reducing income and racial stratification within the metropolitan area. Using a structural model of neighborhood choice with endogenous rents and demographic composition, I quantify the welfare consequences for unsubsidized households without vouchers. High-income households experienced modest welfare losses from higher housing costs, while unsubsidized low-income households benefited from lower rents and reduced exposure to concentrated poverty. Although housing vouchers themselves impose welfare costs on unsubsidized low-income households by concentrating demand in low-rent areas, I show that the design that provides greater access to high-opportunity neighborhoods substantially mitigates these losses. Relative to uniform metropolitan subsidy caps, SAFMR spreads the welfare incidence of housing assistance more evenly across the income distribution.

JEL Codes: H75, I38, J15, R13, R23, R28

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1 Introduction

Low-income, minority households disproportionately reside in neighborhoods with limited economic resources and opportunities, a defining feature of many U.S. cities (Aliprantis et al., 2022; Bayer et al., 2021; Reardon et al., 2015).[1] Surprisingly, this pattern is especially pronounced among households receiving housing assistance (Collinson et al., 2015; Galvez, 2010; Horn et al., 2014; Mazzara and Knudsen, 2019; Metzger, 2014; Rosen, 2020). As research has established that neighborhoods are critical in shaping economic, educational, and health outcomes for both adults and children, this pattern of residential segregation has important implications for inequality, intergenerational mobility, and even long-run racial convergence (Bayer et al., 2025; Chetty et al., 2026; Chetty and Hendren, 2018; Chetty et al., 2020; Chyn and Katz, 2021).[2]

In response, considerable policy debates have increasingly focused on improving low-income households' access to opportunity-rich neighborhoods.[3,4] A large body of research studies whether specific policies or designs succeed in changing where beneficiaries live and how they benefit. However, far less is known about the broader equilibrium effects of mobility-oriented policies when they operate at scale. Large inflows of low-income households into traditionally high-price, high-income neighborhoods may generate indirect equilibrium effects on prices, demographic composition, and other local amenities through household re-sorting and subsequent changes in

[1] There are well-documented mechanisms through which such segregation pattern arises, including decentralized racial sorting (Bayer and McMillan, 2005; Shertzer and Walsh, 2019), discrimination in the housing market (Ahmed and Hammarstedt, 2008; Bayer et al., 2017; Carlsson and Eriksson, 2014; Christensen et al., 2021; Christensen and Timmins, 2022, 2023; Ewens et al., 2014; Hanson and Hawley, 2011; Hanson et al., 2016; Turner et al., 2016), differences in access to wealth (Aliprantis et al., 2022), and information friction during the housing search (Bergman et al., 2020; Ioannides, 2011).

[2] See also Aliprantis and Richter (2020); Chetty et al. (2016); Chyn (2018); Damm and Dustmann (2014); Katz et al. (2001); Kling et al. (2007, 2005); Leventhal and Brooks-Gunn (2003); Pinto (2021).

[3] Efforts to expand low-income households' access to high-opportunity neighborhoods take a variety of forms. Classic examples include the Moving to Opportunity (MTO) experiment (Chetty et al., 2016; Kling et al., 2007; Ludwig et al., 2012, 2013) and the Gautreaux program (Chyn et al., 2025). More recent initiatives utilize financial incentives and counseling services, such as Creating Moves to Opportunity (CMTO) (Bergman et al., 2024) and the Baltimore Housing Mobility Program (DeLuca and Rosenblatt, 2017). Related research also examines the role of information interventions (Bergman et al., 2020), alternative voucher payment standards (Aliprantis et al., 2022; Collinson and Ganong, 2018), and policies aimed at reducing landlord discrimination (Blanco and Song, 2024; Ellen et al., 2023).

[4] Most recently, Chetty et al. (2026) study a complementary approach that revitalize conditions within high-poverty neighborhoods themselves rather than relocating people to high-opportunity neighborhoods.

endogenous amenities. These changes may well affect the welfare of many households beyond the direct beneficiaries of such mobility programs.

This paper examines how expanding low-income households' access to high-rent neighborhoods at scale affects the residential equilibrium. I study the Small Area Fair Market Rent (SAFMR) reform, a major redesign on the Housing Choice Voucher (HCV) program that replaces a single metro-wide voucher payment standard with ZIP code-specific rent ceilings that are higher in expensive areas and lower in cheaper ones (Dastrup et al., 2018).[5] By effectively increasing housing supply available to voucher households in high-rent areas and reducing it elsewhere, SAFMR induces a large relocation of voucher households from low- to high-rent areas (Collinson and Ganong, 2018; Ellen et al., 2025; Eriksen et al., 2024). This feature makes SAFMR a particularly useful setting for thinking about the equilibrium consequences of policies that improve low-income households' access to more expensive, high-opportunity neighborhoods.

I adopt a difference-in-differences design comparing the Dallas metropolitan area, the first to adopt SAFMR in 2011, to a set of metros that adopted the policy later in 2018 and exhibit similar pre-policy patterns of voucher usage and concentrated poverty.[6,7] As a first stage, I confirm that SAFMR triggered a sizable shift in voucher usage toward high-rent neighborhoods. Six years after policy implementation, the number of voucher households in these areas increased by more than 40 percent, with some census tracts experiencing increases from nearly zero to over 200 voucher households within a decade, making up a substantial share of the local renter-occupied housing stock.

This geographical redistribution of voucher demand had pronounced effects on the residential equilibrium. Rent prices became more *polarized*: increased demand in high-rent neighborhoods raised market rents, while reduced demand in low-rent neighborhoods lowered them. In particular, rent declines within low-rent neighborhoods were concentrated in the upper segment of the local

[5] HCV, commonly known as Section 8, is the largest tenant-based federal housing policy in the U.S., serving about 2.8 million households to find homes in the private rental market.

[6] The Dallas metropolitan area in this research setting refers to Dallas-Plano-Irving, TX metro division.

[7] SAFMR began on October 1, 2010, in Dallas. I refer to this period as 2011 throughout to match HUD's fiscal year description.

rent distribution, where voucher households had previously been most likely to lease units but were no longer able to do so under the lower payment standards.[8]

At the same time, SAFMR led to a more *integrated* residential equilibrium in terms of income and racial composition. The share of low-income and Black households increased in high-rent neighborhoods, while the share of high-income and White households increased in low-rent neighborhoods. Using proprietary data on households' residential histories, I find suggestive evidence that, as voucher households entered high-rent neighborhoods and rents rose, some unsubsidized higher-income households relocated toward lower-rent areas. I also observe increased relocation flows among high-rent neighborhoods, suggesting that some higher-income households re-optimized their locations by substituting toward other high-rent neighborhoods that experienced smaller voucher inflows. Together, these changes reduced income and racial segregation across neighborhoods, even as rent prices diverged.

Motivated by these empirical patterns, I develop and estimate a household sorting model with endogenous rent prices and neighborhood demographic composition, combined with a calibrated housing supply function, following the framework of Almagro et al. (2023), to assess the welfare implications of the observed equilibrium changes. The model allows households' preferences over neighborhood characteristics to vary by income group, capturing the distinct relocation margins across the income distribution documented in the earlier empirical analysis. This structure enables the model to reflect the key channels through which the relocation of voucher households to high-rent neighborhoods affects welfare for *unsubsidized* households across the board in equilibrium.

Using the estimated model, I find that SAFMR led to heterogeneous welfare effects for unsubsidized households across the income distribution. Unsubsidized high-income households experienced modest welfare losses, on the order of 0.1 to 0.2 percent of their annual income. For households in the highest income quartile, these losses are driven primarily by higher rents, while

[8] The rent results are closely related to Eriksen and Ross (2015) who study the effects of a large increase in voucher supply and find little impact on the overall market rents. In contrast to their setting, which examines an *overall* increase in the number of vouchers issued at the metro level, SAFMR primarily reallocates voucher demand *across* neighborhoods within a metro. The authors, however, do observe rent increases for units near the payment standard, suggesting that voucher households respond to payment caps in ways that can generate localized price effects at specific points in the rent distribution.

for households in the third quartile, they reflect a combination of rising rents and changes in neighborhood composition. In contrast, unsubsidized low-income households experienced substantial welfare *gains*. For households in the lowest income quartile, welfare increased by about 0.6 percent of annual income from both lower rents and changes in neighborhood composition. All these differences are consistent with distinct relocation margins across income groups documented in the reduced-form analysis.

To assess how the welfare incidence of the voucher program depends on its design, I use the estimated model to compare two voucher payment designs—a traditional metro-level payment cap and a ZIP code-level payment cap—to a counterfactual equilibrium without any voucher program. Comparing the traditional metro-level design to the no-voucher counterfactual shows that this design imposes large welfare losses on the unsubsidized lowest-income households, accounting to 2.9 percent of their annual income. This occurs because, under metro-wide payment standards, voucher demand is concentrated in the same low-rent neighborhoods where the poorest unsubsidized households typically reside. Replacing the traditional design with SAFMR nearly halves the welfare loss borne by the unsubsidized lowest-income households, reducing it to 1.5 percent of income. By shifting voucher demand toward higher-rent neighborhoods, SAFMR spreads the welfare burden of the voucher program more evenly across the income distribution. These findings suggest that localized payment standards can not only improve access for voucher recipients but also reduce the regressive incidence of housing assistance on unsubsidized low-income households, the very population this program is aimed to assist.

Taken together, the welfare results pose two broader lessons about the voucher program and its design. First, instituting a voucher program imposes meaningful welfare costs on unsubsidized low-income households who are not part of the program, the very population the program is intended to assist (Susin, 2002). Importantly, this negative incidence arises under both metro-wide and neighborhood-level payment standards. Second, conditional on implementing a voucher program, neighborhood-level payment standards substantially alter the distribution of this burden. Relative to traditional metro-wide payment caps, SAFMR spreads the welfare costs of the program more evenly across the income distribution, reducing the concentration of welfare losses among the poorest, unsubsidized households. In this sense, SAFMR can be viewed as a much more progressive version of implementing the voucher program. While it expands access to high-opportunity neighborhoods for voucher recipients with heavier subsidies, it also indirectly lowers housing costs for unsubsidized low-income households in low-rent areas, at the expense of modest welfare losses among higher-income households. These considerations are particularly relevant in light of the limited funding of the voucher program and the long waiting lists it generates, which leaves many voucher-eligible low-income households without assistance for extended periods (Acosta and Gartland, 2021).[9]

This paper contributes to the broader literature studying how housing policies shape local housing markets and residential equilibrium. A large body of work examines how place-based housing interventions affect rents, neighborhood composition, and welfare in general equilibrium. This includes studies of affordable housing construction through the Low-Income Housing Tax Credit (Baum-Snow and Marion, 2009; Davis et al., 2023; Diamond and McQuade, 2019; Eriksen and Rosenthal, 2010), as well as work on rent regulation and its spillovers, including the introduction and removal of rent control (Autor et al., 2014, 2017; Diamond et al., 2019). Related research examines alternative affordability measures taken by non-profit organizations, such as Community Land Trusts, and their effects on neighborhood composition and housing markets (Ali and Raviola, 2025). More recently, Almagro et al. (2023) study the general equilibrium effects of public housing demolitions in Chicago, documenting changes in neighborhood characteristics and welfare across demographic groups. Closer to the voucher context, Galiani et al. (2015) and Davis et al. (2021) analyze settings in which voucher use is geographically restricted. In contrast, I study a policy environment in which voucher households face fewer locational constraints and experience enhanced access to high-opportunity neighborhoods, allowing me to examine how large-scale mobility affects residential equilibrium when households can freely re-sort across space.

Second, this paper contributes to the growing literature on HCV, with particular emphasis on

[9]The Philadelphia Housing Authority (one of the major Public Housing Authorities operating in metros required to adopt SAFMR), for example, reopened its HCV waiting list in January 2023 for the first time in more than 12 years. Even then, only 2,000 vouchers were immediately available. This illustrates the severity of excess demand and the prolonged rationing of vouchers in most metropolitan areas (Philadelphia Housing Authority, 2023).

SAFMR reform. Existing research has primarily focused on the direct effects of voucher policy on participating households and landlords. A number of studies examine voucher take-up, lease-up, and sorting behavior among voucher recipients (Collinson and Ganong, 2018; Dastrup et al., 2019; Ellen et al., 2025, 2023; Eriksen et al., 2024; Horn et al., 2014; Mazzara and Knudsen, 2019; Reina et al., 2019). Others study landlord responses to vouchers, including pricing behavior and discrimination against voucher holders (Aliprantis et al., 2022; Eriksen and Ross, 2015; Olsen, 2019; Phillips, 2017), whereas Park (2025) examines the implications of SAFMR on the overall program costs under SAFMR. Building on this work, I move beyond the direct participants in the voucher market to study how the reallocation of voucher households induced by SAFMR reshapes neighborhood rents and demographic composition through the joint sorting decisions of voucher and non-voucher households. In doing so, the paper provides new evidence on the unintended welfare consequences of voucher design for households that do not receive assistance.

Lastly, this paper contributes to the literature using structural models of neighborhood choice to study household sorting and welfare (Bayer et al., 2007; Bayer and McMillan, 2005; Bayer et al., 2016, 2004; Fu and Gregory, 2019; Wong, 2013). My model is closely related to papers incorporating endogenous neighborhood changes in response to various local shocks (Almagro et al., 2023; Almagro and Dominguez-Iino, 2022; Couture et al., 2023; Guerrieri et al., 2013; Qian and Tan, 2021).

The remainder of the paper proceeds as follows. Section 2 lists the institutional background of HCVP and SAFMR and how the maximum subsidy amounts are set for each ZIP code under the new policy. Section 3 illustrates the economic mechanisms through which SAFMR changes the residential equilibrium in the long run. Section 4 lists the data sources for the empirical analyses throughout the paper. Section 5 describes the empirical strategies adopted and the empirical results. Section 6 presents a model of residential sorting by non-voucher households, and Section 7 uses the estimated model to perform welfare analysis of the policy. Section 8 summarizes and concludes with the discussion about the significant impact of HCVP and SAFMR on the local economy that goes beyond the immediate recipients of the policy.

2 Institutional Background

The Housing Choice Voucher (HCV) program, commonly referred to as Section 8, was enacted in 1974 to assist low-income families in affording safe and sanitary housing in the private rental market. The program is administered by the Department of Housing and Urban Development (HUD), and it provided over 2.7 million low-income families with affordable homes in 2023. HUD allocated \$32.1 billion to the HCV in 2023 out of the total budget of \$71.9 billion requested by the President's Budget, making it the largest federally run tenant-based housing subsidy program in the United States.[10]

The voucher households generally pay about 30% of their income toward rent and the remaining balance is paid by the voucher. The maximum subsidy amount for each region is capped at the payment standard which is set by each Public Housing Authority (PHA).[11] HUD first calculates the fair market rents (FMR) based on the 40th percentile of the gross rent for each region and bedroom size. The PHAs then decide the exact payment standards, which would serve as the effective rent caps for voucher holders, to fall anywhere between 90% and 110% of the HUD-proposed FMRs at their own discretion, taking local housing market conditions into consideration.

In principle, this structure of the program gives voucher households broad locational choice within a metropolitan area. Because the tenant's required rent contribution depends only on income rather than unit price, households are largely price-insensitive below the payment cap. This means the voucher households essentially have the freedom to locate anywhere within in region as long as they can lease an appropriately priced rental unit in the private market.[12]

In practice, however, the traditional design of FMRs substantially constrains voucher households' access to high-rent, high-opportunity neighborhoods. Historically, FMRs have been set

[10] https://www.hud.gov/sites/dfiles/CFO/documents/2023_BudgetInBriefFINAL.pdf

[11] Voucher households are allowed to rent units that are priced about the payment standard. However, they are prohibited from paying more than 40% of their income.

[12] For example, a voucher household earning \$1,000 per month pays \$300 toward rent regardless of whether the unit rents for \$900 or \$1,200, as long as the price of the unit does not exceed the set payment standard. If the payment standard is, for example, \$1,300 and the household leases a \$1,400 unit, the households then must cover the excess \$100 in addition to the standard 30 percent contribution, raising its total rent payment to \$400. In practice, however, this rarely happens.

at the metropolitan level, typically corresponding to Core-Based Statistical Areas (CBSA), limiting FMRs' variability across neighborhoods.[13,14] These metropolitan-wide FMRs (MFMRs), thus, compress within-metro rent variation into a single benchmark. As a result, payment standards tend to be generous relative to prevailing market rents in low-rent neighborhoods and restrictive in high-rent neighborhoods. This mechanically constrains voucher-eligible housing supply in high-rent neighborhoods, effectively steering voucher households toward low-rent, low-opportunity areas where eligible units are more abundant.

Concerns about the exclusionary effects of MFMRs were central to the Walker v. U.S. HUD litigation, which ruled that metropolitan-wide rent caps in the Dallas area unlawfully limited voucher families' access to predominantly White, higher-rent neighborhoods.[15] In response, HUD introduced Small Area Fair Market Rents, which set FMRs at the ZIP code level rather than the metropolitan level. Under SAFMR, the ZIP code-specific FMR is calculated by multiplying the CBSA-level two-bedroom FMR by a rental rate ratio, defined as the ratio of median gross rent in the ZIP code to median gross rent in the CBSA.[16] This new approach more closely aligns rent caps with local market conditions and expands the set of voucher-eligible units in high-rent neighborhoods.

In 2018, HUD expanded the mandatory adoption of SAFMR to 24 additional metropolitan areas nationwide with the plan to extend to additional metropolitan areas every five years starting in 2025. Eligibility for mandatory implementation was determined using five criteria: (1) a minimum of 2,500 HCVP units under contract, (2) at least 20% of standard-quality rental stock located in ZIP codes where SAFMR is more than 110% of the metropolitan-wide FMR, (3) the percentage of voucher families living in low-income areas must be at least 25% of all renters within the area, (4) the ratio of the percentage of voucher holders living in low-income areas to the percentage of all renters in entire metropolitan area exceeds 1.55, and (5) the vacancy rate for the metropolitan area is higher than 4% (SAFMR Final Rule Criteria Notice; Docket No. FR–5855–F–03). These

[13] Metro-level FMRs are—roughly speaking—set at the 40th percentile of the gross rent distribution of an entire metropolitan area.

[14] In non-metropolitan areas, FMRs are set at the county level.

[15] https://www.danielbesharalawfirm.com/walker-v-hud-dallas-public-housing-desegregation

[16] See Section II of Docket No. FR–5413–N–01 for a detailed description of the SAFMR methodology.

later-selected metropolitan areas to adopt the policy will serve as an important control group in the empirical analysis to follow in the later section.[17] The list of metropolitan areas that met all five criteria is presented in Appendix Table C.1.

3 Expected Long-Run Effects on Residential Equilibrium

The expected equilibrium effects of SAFMR operate through the relocation decisions of both voucher and non-voucher households (i.e., unsubsidized households). In this section, I outline the mechanisms through which the policy reshapes the rental market and residential sorting, and I describe the predicted long-run equilibrium effects. To fix ideas, I abstract from housing supply responses and population growth, assuming a fixed housing supply and a fixed number of households within a metropolitan area throughout this discussion.

The direct effect of SAFMR is manifested through the relocation of voucher households. By expanding the set of rental units that are voucher-eligible in high-rent neighborhoods, the policy enables more voucher households to move into higher-opportunity areas. This increase in voucher demand places upward pressure on rents in these neighborhoods. On the other hand, as voucher households exit lower-rent neighborhoods, demand declines in those areas, leading to downward pressure on rents. These declines are expected to be concentrated in the upper distribution of the neighborhood rent, where voucher households were previously most likely to lease units. Taken together, the expected direct effect of the policy raises rents in high-rent, high-opportunity neighborhoods and lowers rents in low-rent, low-opportunity neighborhoods.

Indirect effects emerge as non-voucher households respond to these changes in prices and demographic composition of neighborhoods. Higher rents make high-opportunity neighborhoods less affordable for some unsubsidized households. At the same time, changes in the demographic composition of neighborhoods—such as increases in the share of low-income and minority resi-

[17]HUD initially selected 31 metropolitan areas that met all five criteria. However, in practice, the policy became effective only in 24 (out of the initial 31) metropolitan areas. The final selection rule of the 24 metropolitan areas still remains in the dark with no clear explanations offered from HUD.

dents—may also affect residential choices if households value the characteristics of their neighbors (Bayer et al., 2025). These changes may induce some incumbent households in high-rent neighborhoods to re-optimize their locations and may deter potential in-migrants who would have chosen these neighborhoods in the absence of the policy.

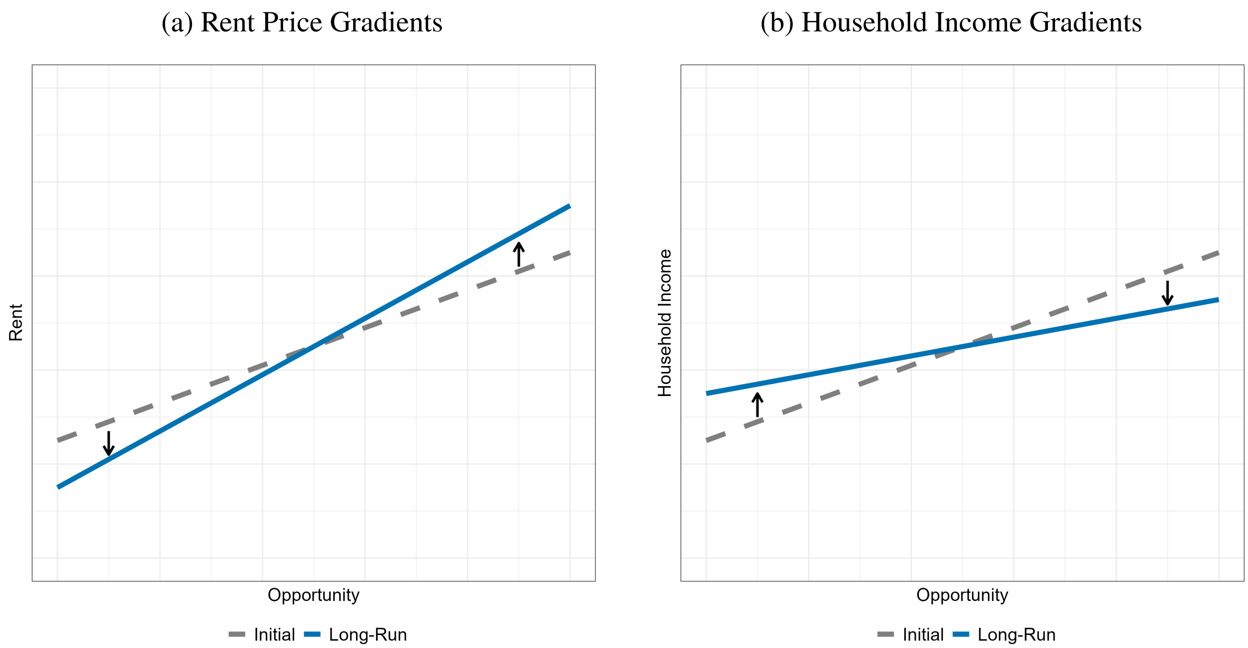
The subsequent residential re-optimization among non-voucher households can take two main forms. A subset of households may remain in high-rent neighborhoods by substituting toward even higher-rent neighborhoods that not many or no voucher households enter. This adjustment places additional upward pressure on rents in the upper tail of the local rent distribution within high-rent neighborhoods. Other households—often relatively lower-income within the high-income group—are more likely to relocate to lower-rent neighborhoods that better align with their budget constraints given the post-policy increase in market rents. These moves modestly increase demand in lower-rent neighborhoods, particularly for units near the upper end of the rent distribution in those areas. All in all, these indirect responses through non-voucher households' re-sorting may reinforce rent polarization: high-rent neighborhoods become more expensive, while market rents in low-rent neighborhoods remain lower or rise only modestly at the upper end.

I summarize the combined effects on rent prices in the left panel of Figure 1 which plots hypothetical rent gradients across neighborhoods ranked by "opportunity," proxied (in this research setting) by neighborhood-level FMR.[18] The dashed gray line depicts the pre-policy equilibrium, in which rents increase with neighborhood opportunity. Following the policy change, rents rise in high-opportunity neighborhoods and fall in low-opportunity neighborhoods, causing the rent gradient to tilt counterclockwise in the long run. The shift illustrates how SAFMR generates a more *polarized* rent equilibrium, making expensive neighborhoods more expensive and cheap neighborhoods cheaper.

In contrast to rent prices, the long-run effects of SAFMR on neighborhood income composition imply a more integrated, egalitarian equilibrium. The direct effect of the policy increases the share of low-income households in traditionally high-income, high-rent neighborhoods. Indirectly,

[18] An empirical analogue of these predicted equilibrium changes is presented in Appendix Appendix C.

Figure 1: Expected Effects of SAFMR on Residential Equilibrium



Notes: The figures above show the expected changes to the rent price gradient (left panel) and household income gradient (right panel) plotted with respect to neighborhood opportunity percentiles. Dashed gray lines represent the pre-policy equilibrium, and solid blue lines represent the predicted long-run equilibrium.

some higher-income households displaced by rising rents and changing neighborhood composition re-optimize by relocating to lower-rent neighborhoods than they would have chosen in the absence of the policy. As shown in the right panel of the figure, these forces tilt the household income gradient clockwise. A flatter gradient relative to the pre-policy equilibrium indicates a more even distribution of household income across neighborhoods.

Given the strong correlation between income and race in the United States, these changes in income sorting also imply shifts in racial composition. The inflow of minority households into high-rent neighborhoods and the outflow of non-minority households toward lower-rent neighborhoods increase racial diversity across neighborhoods. As a result, neighborhoods that were previously dominated by non-minority become more racially diverse, while neighborhoods with traditionally high share of minority residents see an increase in non-minority residents. In this way, SAFMR is expected to reduce residential segregation and generate a more racially integrated long-run equilibrium.

4 Data

The primary neighborhood-level data used in this study come from publicly available ZIP code- and Census tract-level aggregates from the 5-year American Community Surveys (ACS) (various years), accessed via the National Historical Geographic Information System (NHGIS) (Manson et al., 2022). The main variables used in the analysis include the 25th-, 50th, and 75th-percentile contract rents, as well as the number of households by race in each geographical unit. To better characterize the number of households by income within ZIP codes, I supplement the ACS with ZIP code-level income data from the Statistics of Income (SOI) tax statistics from the Internal Revenue Service (IRS).

Data on FMRs at both the metropolitan and ZIP code levels are obtained from HUD. For each fiscal year, HUD publishes FMR values for all metropolitan areas, counties, and ZIP codes nationwide, regardless of whether the payment standards are set at the metropolitan or ZIP code level in a given area. As a result, ZIP code-level FMRs represent hypothetical payment standards in areas operating under metro-wide FMRs, and vice versa. I use these measures to classify neighborhoods by "opportunity" type, as described in Section 4.1.

Information on the number of voucher households at various geographical definitions is drawn from HUD's publicly available Picture of Subsidized Households (PoSH) data. Census tract-level PoSH data are available for the full analysis period, though Census tract definitions change from 2000 to 2010 boundaries in 2012. On the other hand, ZIP code-level PoSH data are available from 2017 onward. To construct consistent ZIP code-level measures prior to 2017, I harmonize tract-level PoSH data to ZIP code boundaries. All tract-level measures are standardized to 2010 Census geography. The procedure to make these geographical definitions is described in detail in Appendix A.

To document household-level residential mobility, I use proprietary data from InfoUSA's Residential Historical Database. This dataset tracks approximately 120 million households nationwide from 2006 onward and includes information on residential address histories, estimated household income and wealth, imputed renter or owner status, and ethnicity. The availability of exact address information allows me to observe household moves within and across neighborhoods over time and to examine relocation patterns before and after SAFMR implementation.

4.1 Defining Opportunity Status for Each Neighborhood

As discussed in Section 2, HUD publishes FMRs for each ZIP code, and PHAs set the exact voucher payment standards. These payment standards represent the actual maximum rent cap that a voucher will cover as anything above this threshold must be paid out of pocket by the household. PHAs are required to set payment standards within a range of 90 to 110 percent of the HUD-published FMR. While ZIP code-level FMRS are publicly available nationwide, the exact payment standards locally adopted by PHAs are difficult to observe systematically. These standards were distributed locally though mailings or posted on individual PHA websites, and no comprehensive archive exits. Given this constraint, I define neighborhood opportunity status using the publicly available ZIP code-level FMRs from HUD.[19,20]

Throughout the paper, I classify ZIP codes as *high-opportunity* if their ZIP code-level FMRs under SAFMR in 2011, evaluated at the lower bound of the allowable payment standard (90 percent of the HUD-published FMR), exceed the traditional Dallas-wide FMR in 2011. These ZIP codes therefore experienced a substantial increase in effective payment standards following SAFMR adoption, expanding the set of rental units eligible for voucher use. In contrast, *low-opportunity* ZIP codes are those for which the upper bound of the ZIP code-level FMR (110 percent of the HUD-published value) falls below the metro-wide FMR. These neighborhoods experienced reductions in effective payment standards, shrinking the set of voucher-eligible units. The remaining ZIP codes, for which the metro-wide FMR lies between the lower and upper bounds of the ZIP code-level FMR, are classified as *mid-opportunity*. In these areas, SAFMR had little impact on the payment

[19] Ideally, one would observe the exact payment standards chosen by the PHA for each ZIP code and directly classify neighborhoods based on whether their payment standards increased or decreased relative to the pre-SAFMR metro-wide standard.

[20] Note that all opportunity classifications are based on two-bedroom FMRs, which correspond to the most common unit size leased under the voucher program. Results are nearly identical when opportunity status is defined using three-bedroom FMRs. Two- and three-bedroom ZIP code–level FMRs are highly correlated, leading to very similar classifications across neighborhoods.

standards and, consequently, minimal change in voucher eligibility of rental units.

In this research context, the term "opportunity" is used to classify neighborhoods based on relative rent levels within a metropolitan area. This definition closely aligns with recent work by Aliprantis et al. (2022), who define "opportunity landlords" as those operating in higher-rent neighborhoods. While this measure does not directly capture other commonly used definitions of neighborhood opportunity—such as intergenerational mobility rates (Chetty et al., 2026) or poverty rates emphasized in the MTO literature—I document strong correlations between rent-based opportunity measures and these alternative indicators in Appendix C. As a result, the qualitative implications of the analysis are likely robust to alternative definitions of neighborhood opportunity.

ZIP codes are the most natural definition of "neighborhoods" in this setting as FMRs and payment standards are defined at the ZIP code level. However, depending on data availability and the level of analysis, I use the term "neighborhoods" flexibly to refer to either ZIP codes or census tracts, and I will explicitly state the geographic unit used in each context. When the analysis is conducted at the tract-level, assigning opportunity status requires additional consideration since FMRs are defined by ZIP codes and census tracts may overlap multiple ZIP codes. I classify a census tract as high-, mid-, or low-opportunity based on the opportunity status of the ZIP code that contains the majority of the tract's residential population.

4.2 Summary Statistics

In this section, I provide some summary statistics on the characteristics of neighborhoods (defined using tracts) in Dallas and the metropolitan area itself in Table 1. Panel A of the table first illustrates the total number of households and voucher households in Dallas and also the numbers by neighborhood opportunity status. The total number of households increased in Dallas from 1.4 million in 2010 to 1.7 million in 2019 with an increasing share of households living in rental units from 38.5% to 42.1% among all households. Such increases are consistent among all high-, mid-, and low-opportunity neighborhoods. Voucher households made up about 5.9% of the renter-occupied housing units in 2010 and 4.8% in 2019. Black households are the predominant majority of the voucher population making up approximately 80% of the total with Hispanic households consisting of about 6%.

The growth of the voucher population was 4.5% and did not match the growth of the overall population of 17.8% in Dallas. However, it is important to note how the number of voucher households changed in each opportunity neighborhood. The number of voucher households increased in high-opportunity neighborhoods by about 3,000 corresponding to a 54% growth, whereas the numbers declined by 6% and 11% in mid- and low-opportunity neighborhoods, respectively. This descriptively accounts for the effectiveness of the policy successfully relocating voucher households to move to higher-opportunity neighborhoods.

To visualize the spatial dimension of these patterns, Figure 2 maps census tracts in the Dallas metropolitan area. The left panel shows median gross rent of tracts (based on 2015-2019 ACS). High-rent, high-opportunity neighborhoods are concentrated primarily in the northwestern part of the metro, while mid-opportunity neighborhoods largely surround the urban core. Low-rent, lop-opportunity neighborhoods are concentrated in the central city and in peripheral areas to the south and east.

The right panel maps changes in the number of voucher households between 2010 and 2019. The spatial redistribution of voucher households is visually striking. Many low-rent neighborhoods uniformly experienced substantial declines in voucher usage, while higher-rent neighborhoods saw sizable increases. Importantly, voucher inflows into high-opportunity neighborhoods were highly uneven. Some neighborhoods experienced little to no change, while other saw large increase in the number of voucher households. In one census tract in Kaufman County, for example, the number of voucher households increased by 296, accounting for roughly 84 percent of all renter-occupied units in 2019. These relocation of voucher take-ups foreshadows changes in endogenous neighborhood composition examined in subsequent sections.

Table 1: Summary Statistics of Census Tracts in Dallas-Plano-Irving, TX Metro Division

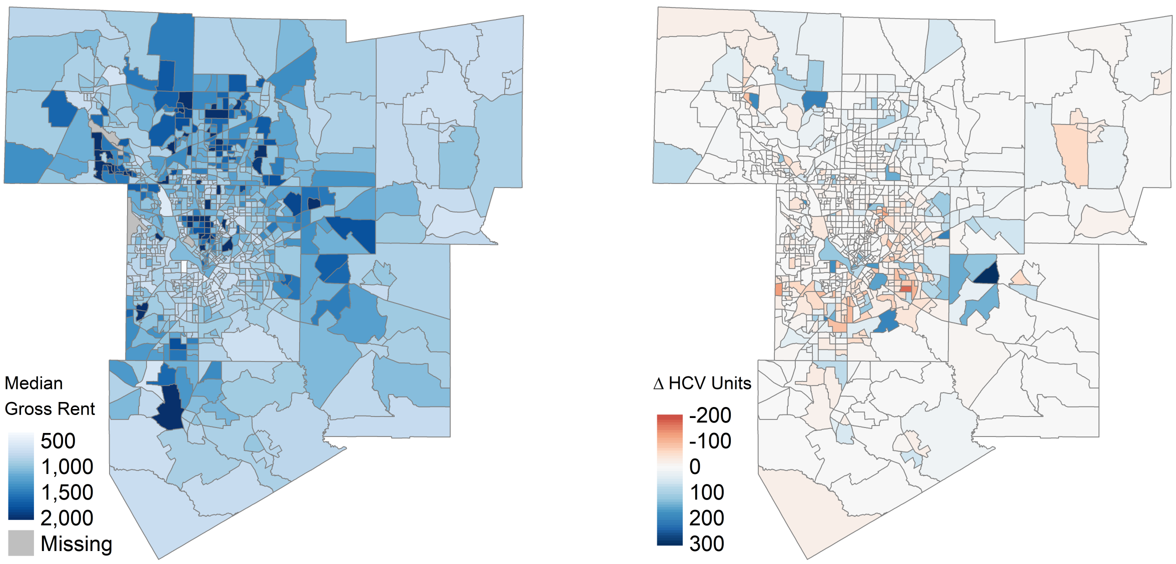
	All Neighborhoods		High Opportunity		Mid Opportunity		Low Opportunity	
	2010	2019	2010	2019	2010	2019	2010	2019
Panel A: Aggregate Summary Statistics								
Total Households[a]	1,462,057	1,721,276	602,652	763,519	541,166	599,685	318,239	358,072
Owner-Occupied	898,449	996,511	399,270	472,034	320,829	336,488	178,350	187,989
Renter-Occupied	563,608	724,765	203,382	291,485	220,337	263,197	139,889	170,083
Total Voucher Households[b]	33,175	34,680[c]	5,481[e]	8,455[e]	12,699[e]	11,951[e]	14,920[e]	13,287[e]
Share Black (%)	80	81[d]	-	-	-	-	-	-
Share Hispanic (%)	6	6[d]	-	-	-	-	-	-
Panel B: Average Summary Statistics								
Households[a]	1,630	1,919	1,693	2,145	1,670	1,851	1,467	1,650
	(691)	(956)	(728)	(1087)	(684)	(876)	(615)	(735)
Owner-Occupied Units[a]	1,002	1,111	1,122	1,326	990	1,039	822	866
	(660)	(853)	(673)	(951)	(692)	(813)	(540)	(631)
Renter-Occupied Units[a]	628	808	571	819	680	812	645	784
	(542)	(674)	(597)	(774)	(512)	(615)	(483)	(576)
Median Household Income[a] ($)	64,362	78,408	84,701	100,653	58,442	73,068	39,818	49,992
	(35,304)	(40,583)	(35,390)	(39,905)	(29,773)	(35,796)	(21,162)	(25,124)
Median Gross Rent[a] ($)	1,017	1,315	1,200	1,570	968	1,256	793	987
	(347)	(446)	(363)	(447)	(299)	(391)	(200)	(216)
Median Home Value[a] ($)	181,384	259,131	238,491	345,762	171,409	240,264	103,620	144,111
	(133,819)	(209,583)	(151,164)	(231,385)	(114,495)	(171,306)	(7,4769)	(154,384)
Share Black[a] (%)	16.55	17.92	9.51	11.91	16.05	17.81	28.89	27.92
	(20.80)	(19.97)	(9.87)	(11.19)	(17.24)	(18.21)	(30.93)	(28.14)
Share Hispanic[a] (%)	21.72	24.31	12.10	13.24	24.45	28.00	33.42	36.93
	(20.00)	(20.80)	(9.64)	(9.66)	(18.42)	(20.00)	(26.45)	(25.69)
Share White[a] (%)	55.09	49.09	68.05	60.89	53.91	47.17	35.54	32.63
	(26.56)	(26.23)	(16.46)	(18.14)	(23.60)	(24.79)	(31.41)	(29.79)
Share College+[a] (%)	33.29	36.62	47.61	51.37	30.33	33.35	14.21	17.37
	(22.56)	(23.34)	(19.33)	(18.51)	(20.39)	(22.01)	(12.64)	(15.02)
Share Poverty[a] (%)	12.55	11.54	6.43	6.66	12.40	11.05	22.84	20.27
	(11.08)	(9.24)	(6.09)	(5.12)	(8.77)	(7.26)	(12.87)	(10.76)
Number of Tracts	897		356		324		217	

Notes: The table above shows various summary statistics of neighborhoods in the Dallas metropolitan area in 2010 and 2019. The upper panel shows the aggregate statistics of the number of total households and voucher households in Dallas and in different opportunity neighborhoods. The lower panel shows the average neighborhood characteristics in the metropolitan area as a whole and also separately by neighborhood opportunity types. Superscript *a* indicates the data come from 5-year ACS; *b* indicates the data come from the Picture of Subsidized Households; *c* indicates that the number is inferred using the previous ratio of voucher households living in the Dallas part of the metro and the Fort Worth part of the metro; *d* indicates the numbers come from 2016 Picture of Subsidized Households data; and *e* indicates that the numbers are aggregated from tract-level PoSH data with some tracts with low number of voucher households being censored. For ACS data, the years 2010 and 2019 represent 2006-2010 and 2015-2019 ACS, respectively. For Picture of Subsidized Households data, the years 2010 and 2019 represent the years listed unless explicitly mentioned. The dollar amounts are displayed in each respective year's dollar. Standard deviations are in parentheses.

Figure 2: Census Tracts in Dallas Metropolitan Area and Voucher Usage

(a) Median Gross Rent

(b) Change in Voucher Households (2010-2019)



Notes: The figures above show maps of Census tracts in Dallas based on the 2010 geographical designation. The left panel shows the median gross rent of each neighborhood, and the right panel depicts the change in the number of voucher households in each tract from 2010 to 2019.

5 Empirical Analysis

5.1 Redistribution of Voucher Households Across Neighborhoods

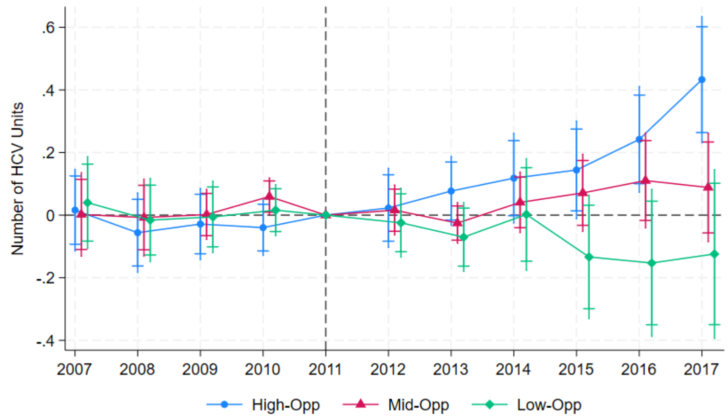
I begin by documenting how voucher take-up across neighborhoods in Dallas changed following the introduction of SAFMR. This analysis revisits and confirms earlier findings that the policy led to increased voucher usage in higher-opportunity neighborhoods. I employ a standard difference-in-differences framework that compares changes in voucher take-up in Dallas neighborhoods to those in metropolitan areas that adopted SAFMR later in 2018.[21]

More specifically, the estimating equation is given by:

$$Y_{jt} = \alpha_j + \alpha_t + \sum_{\tau=-4}^{6} \beta_\tau \times \mathbb{I}_{jt}[t - t^* = \tau,\ m(j) = 1] + \varepsilon_{jt} \tag{1}$$

[21] The control group includes all HUD metropolitan areas listed in Table C.1, excluding the Dallas-Plano-Irving, TX metro division itself.

Figure 3: Change in the Number of Voucher Households



Notes: The figure plots the difference-in-differences coefficients for the number of HCVP voucher households in the high-, mid-, and low-opportunity neighborhoods. The standard errors are robust and clustered at the ZIP code level. Both 90 and 95 percent confidence intervals are shown in the figure.

where Y_{jt} denotes the (log) number of voucher households residing in ZIP code j in year t. The terms α_j and α_t are ZIP code and year fixed effects, respectively. The indicator variable equals one if the observation pertains to τ years relative to the treatment year t^* (2011) and if ZIP code j is located in Dallas (i.e., $m(j) = 1$). The coefficients β_τ are the parameters of interest, tracing out the dynamic effects of SAFMR. The coefficient in the treatment year ($\tau = 0$) normalized to zero. The analysis period ends in 2017 since the control metropolitan areas adopt SAFMR in 2018 and therefore no longer serve as a valid control group. I estimate Equation (1) separately for high-, mid-, and low-opportunity neighborhoods and the estimates are presented in Figure 3.

There is a clear increase in voucher take-up in high-opportunity neighborhoods following the policy change as indicated by the blue circles. By 2017, the number of voucher households in these neighborhoods had increased by more than 40 percent. The adjustment occurs gradually over time, reflecting the fact that households most responsive to SAFMR are often new entrants to the program, while incumbent voucher households may face higher moving costs or be less willing to relocate due to established social and economic ties in their current neighborhoods.

In contrast, low-opportunity neighborhoods, shown by green diamonds, experienced a decline of about 20 percent in the number of voucher households. Although these numbers are statistically insignificant, the point estimates show a downward trend, suggesting the change in the location pattern of voucher households. Voucher take-up in mid-opportunity remains relatively stable over time as shown in red triangles. This pattern is consistent with the minimal change in effective payment standards for these neighborhoods under SAFMR which leaves the availability of voucher-eligible units largely unchanged.

Collectively, these results indicate a substantial redistribution of the voucher population within Dallas following the implementation of SAFMR. This geographical shift provides a key first-stage mechanism through which the policy can affect neighborhood-level rents and demographic composition and sets the stage for the subsequent analysis of equilibrium effects driven by the sorting responses of non-voucher households.

Voucher Concentration and Neighborhood Characteristics

The introduction of SAFMR enabled voucher households to move into higher-opportunity neighborhoods. However, it is unlikely that this increase in take-up was uniform across all high-opportunity neighborhoods (as illustrated in the map in Figure 2). Instead, voucher households may disproportionately relocate to a subset of neighborhoods that better align with their preferences or constraints (Bayer and McMillan, 2005). For example, they may be more likely to relocate to neighborhoods with greater access to public transportation or with higher shares of minority residents, reflecting patterns of racial homophily or other frictions in the housing search process.

To characterize which neighborhood characteristics are correlated with greater voucher inflows, I run the following regression for high-opportunity neighborhoods:

$$\Delta \text{HCVP}_{j,2019-2010} = \beta_0 + \beta_1 \text{SAFMR}_{j,2010} + \beta_2 M_{j,2010} + \beta_3 PT_{j,2010} + \varepsilon_j \tag{2}$$

where the dependent variable is the change in the number of voucher households in tract j between 2010 and 2019. The regressors capture baseline neighborhood characteristics measured prior to SAFMR implementation. These include the newly assigned ZIP code-level FMR under SAFMR

Table 2: Neighborhood Characteristics Related to Voucher Household Movements

	Δ Voucher Households
Fair Market Rent ($)	-0.01
	(0.02)
% Minority	0.20**
	(0.10)
% Commute with Public Transportation	2.52***
	(0.81)
R-squared	0.05
Observations	355

Notes: This table documents the relationship between the change in the number of voucher households and neighborhood characteristics in high-opportunity neighborhoods. Change in the number of voucher households in each Census tract from 2012 to 2019 is regressed on zip code-level fair market rent levels in 2011, share of minority (including Black and Hispanic households) in the 2008-2012 ACS, and share of workers who commute with public transportation in the 2008-2012 ACS.

($SAFMR_{j,2010}$), the share of minority residents (Mj, 2010), defined as the combined share of Black and Hispanic households, and the share of workers commuting via public transportation ($PT_{j,2010}$), which proxies for transit accessibility. Table 2 reports the regression results.

Within high-opportunity neighborhoods, the coefficient on the new ZIP code-level FMR is close to zero and insignificant, suggesting that conditional on access to higher payment standards, voucher households are not necessarily drawn to the highest-rent areas within the high-opportunity group.

However, voucher inflows were positively and significantly associated with both the shares of minority residents and public transportation usage. The strong correlation with minority share is consistent with the demographic composition of the voucher population.[22] The even stronger association with public transportation usage highlights the importance of transit accessibility in shaping voucher households' residential choices. While these correlations may reflect a combination of preferences, discrimination, search frictions, and constraints faced by voucher households, the results show that SAFMR-induced mobility is concentrated in a specific subset of high-opportunity neighborhoods rather than being evenly distributed across them.

[22] 80 percent of the voucher households in Dallas in 2010 were Black and 6 percent of them were Hispanic.

5.2 Change in Rent Prices

The increase in voucher usage in high-opportunity neighborhoods following SAFMR is expected to exert upward pressure on rents in those areas. On the other hand, reduced voucher demand in low-opportunity neighborhoods should place downward pressure on rents there.

To quantify these effects, I again adopt a difference-in-differences framework. However, because ZIP code-level rent data are available only in 5-year ACS aggregates, the analysis relies on a standard two-period, 2×2 difference-in-difference specification:

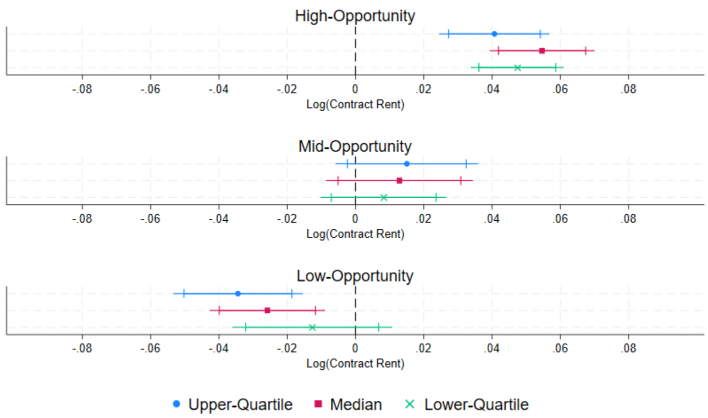
$$Y_{jt} = \alpha_j + \alpha_t + \beta D_{jt} + \varepsilon_{jt} \tag{3}$$

where Y_{jt} denotes the log contract rent in ZIP code j at time t, and D_{jt} is an indicator equal to one for observations in the post-treatment period interacted with an indicator for Dallas neighborhoods. All regressions are weighted by the number of renter-occupied housing units in each ZIP code. This weighting reflects the fact that all voucher households are renters and can only relocate to and from neighborhoods with sufficient rental housing supply where the effects from voucher-induced demand shifts are most likely to materialize. Neighborhoods dominated by owner-occupied single-family housing, for example, offer limited supply of rental supply for voucher entry, making it unlikely that they experience meaningful changes in rental demand or prices.

I use the 2007-2011 ACS at the ZIP code level as the pre-treatment period and the 2013-2017 ACS as the post-treatment period.[23] The model is, again, estimated separately by neighborhood opportunity type and for three points of the rent distribution: the 25th percentile, the median, and the 75th percentile. Identification relies on the standard parallel trends assumption that, absent SAFMR, rent trends in Dallas neighborhoods would have followed those of comparable neighborhoods in control metropolitan areas. While pre-treatment trends cannot be directly assessed at the ZIP code level using ACS data, I provide supporting evidence for parallel trends using metropolitan-level

[23] Ideally, the 2006–2010 ACS would be used to define the pre-treatment period, as the 2007–2011 ACS includes observations from the treatment year (2011). However, the 2007–2011 ACS is the earliest ZIP code–level dataset available.

Figure 4: Contract Rent Prices



Notes: The figure plots the difference-in-differences coefficients for upper-quartile, median, and lower-quartile contract rent changes post-policy by neighborhood opportunity types. The means of the outcomes in the 2007-2011 ACS are presented on the left-hand side of each figure. The regression is weighted by the number of renter-occupied housing units in each ZIP code. The standard errors are robust and clustered at the ZIP code level. Both 90 and 95 percent confidence intervals are shown in the figure.

rent levels in Appendix C. The estimates are presented in Figure 4.

The results show sharp heterogeneity across neighborhoods that are in line with the expectation. In high-opportunity areas, SAFMR increased by around 5 percent across all points in the rent distribution. Mid-opportunity neighborhoods experienced a statistically insignificant increase of 1 to 1.5 percent throughout the distribution. However, low-opportunity neighborhoods saw substantial market rent declines of approximately 3.5 percent in the upper and median distribution, while changes at the lower quartile were statistically insignificant.[24,25]

These patterns closely align with the equilibrium mechanisms outlined in Section 3. In high-opportunity neighborhoods, SAFMR expanded voucher-eligible housing supply, primarily for lower-rent units, increasing demand at the bottom to middle parts of the local rent distribution and pushing up prices there. In low-opportunity neighborhoods, the contraction of voucher-eligible units reduces demand most sharply for higher-rent units and led to price declines at the upper end

[24] These price responses are consistent with findings in Park (2025) which uses the metropolitan areas that adopted SAFMR in 2018 as the treatment group and finds similar distributional rent effects across neighborhoods.

[25] As a supplementary analysis, I apply a distributional synthetic control approach proposed in Gunsilius (2023) to metropolitan-level rent distributions and find comparable distributional shifts following SAFMR adoption: rents increased in the upper tail of the distribution and decline in the lower tail. Details about the method and results are presented in Appendix Section B.3.

of the distribution.

Beyond these direct effects, the results are also consistent with indirect responses by non-voucher households. In particular, incumbent households displaced by rising rents in high-opportunity neighborhoods may substitute toward nearby mid-opportunity neighborhoods, increasing demand and raising rents in those markets (although the coefficients are insignificant). On the other hand, other incumbent households that can afford higher price tags may substitute toward other high-opportunity neighborhoods that experienced smaller voucher inflows and, perhaps, are more expensive than places they used to live. Or they could simply move to more expensive units that are not attainable with vouchers. This potentially shifts demand toward those neighborhoods and units and can put upward pressure on the upper-quartile rents within high-opportunity neighborhoods. Although I do not directly observe these margin, the interpretation is consistent with the relocation pattern I document in the later section.

5.3 Change in Income and Racial Compositions

In this section, I examine how neighborhood demographic composition changed following SAFMR. By design, the policy increases access for low-income households to high-opportunity neighborhoods, which may in turn induce broader re-sorting responses among non-voucher households. To assess these compositional changes, I estimate Equation (3) using ZIP code-level income and racial shares as outcome variables.[26,27] The regression estimates are presented in Figure 5.

The left panel of the figure shows how income composition changed across neighborhoods of different opportunity types following SAFMR.[28] I begin by focusing on households with adjusted gross income below $25,000, a group that includes most voucher recipients. While estimates are only weakly significant due to the limited number of ZIP codes in the analysis, the point estimates

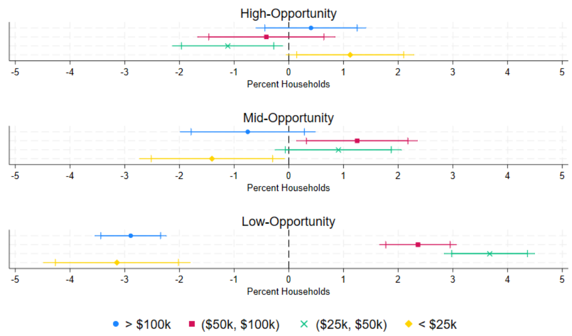
[26]For income composition, I use ZIP code-level SOI data from the IRS in 2010 and 2017 as pre- and post-treatment measures, respectively. Racial composition analysis uses the same ACS data as in the rent analysis.

[27]In Appendix Section C, I show that these moves differ by tenure status and are primarily driven by renters rather than homeowners.

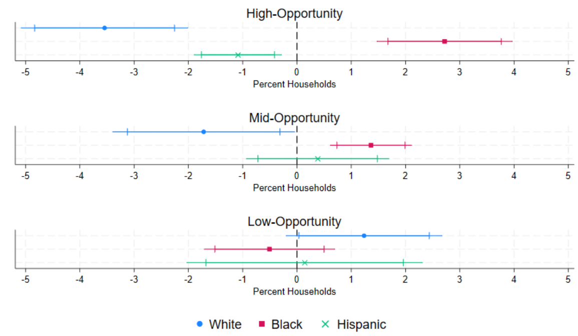
[28]I obtain qualitatively similar patterns using a distributional synthetic control approach in high-opportunity neighborhoods where the data is expected to be the most accurate in capturing the overall population. Details and results are presented in Appendix Section B.

Figure 5: Income and Racial Compositions

(a) Income Compositions



(b) Racial Compositions



Notes: The figures plot the difference-in-differences coefficients for the share of households in different income bins (left panel) and the share of people in different race groups (right panel) by neighborhood opportunity types. The regression is weighted by the number of renter-occupied housing units in each ZIP code. The standard errors are robust and clustered at the ZIP code level. Both 90 and 95 percent confidence intervals are shown in the figures.

are generally consistent with increased entry of low-income households into high-opportunity neighborhoods. The share of households in this income group increased by 1.1 percentage points in high-opportunity neighborhoods, while declining by 1.4 and 3.1 percentage points in mid- and low-opportunity neighborhoods, respectively.

This increase was followed by a decline in the share of households earning between $25,000 and $100,000—especially those earning between $25,000 and $50,000—in high-opportunity neighborhoods, suggesting displacement or re-sorting of non-voucher households. Correspondingly, the share of households earning $50,000-$100,000 increased by 1.2 percentage points in mid-opportunity areas, while the share earning $25,000-$50,000 increased by 1.0 percentage points in the same opportunity neighborhoods. Greater increases in the share of both income groups were observed in low-opportunity neighborhoods, altogether suggesting this consistent story that middle-income households relocating toward lower-opportunity neighborhoods that remain affordable following SAFMR-induced rent changes.

An interesting estimate here is that the share of the highest-income households (those earning above $100,000) remains unchanged in high-opportunity neighborhoods. This suggests that these households are largely insulated from SAFMR-induced changes in rents and neighborhood composition and are willing to absorb higher housing costs in order to remain in high-opportunity locations. In Section 5.4 later, I provide indirect evidence from household-level migration data showing increased relocation flows among high-opportunity neighborhoods, which helps reconcile this estimate as well as the various changes in neighborhood composition presented in this section.

The right panel of the figure documents parallel shifts in racial composition that reflects the income patterns. The share of Black residents increased in higher-opportunity neighborhoods and declined in low-opportunity neighborhoods, consistent with the relocation of predominantly Black voucher households in Dallas. On the other hand, the share of White residents declined in higher-opportunity neighborhoods and increased slightly in low-opportunity neighborhoods. Together, these results indicate that SAFMR led to a more integrated residential equilibrium across neighborhoods in terms of both income and race, operated through the joint re-sorting behaviors from both voucher and non-voucher households.

5.4 Migration Analysis

This section examines household relocation patterns to provide micro-level support for the aggregate neighborhood composition changes documented in the above Section 5.3. Using household-level data from InfoUSA, I analyze how migration patterns within the Dallas metropolitan area evolved following the introduction of SAFMR. I focus on the patterns of people moving *into* areas (i.e., in-migrants) rather than those moving out (i.e., out-migrants) as most scholarly studies agree that shifts in neighborhood composition are predominantly due to variations in in-migration (Asquith et al., 2023; Brummet and Reed, 2021; Ding et al., 2016; McKinnish et al., 2010). In the following analyses, I focus on households who are moving within the metros, abstracting away from considering cross-metro moves.

5.4.1 In-Migrants to Low-Opportunity Neighborhoods

I first examine the characteristics of migrants who are moving into low-opportunity neighborhoods in Dallas by tracking down households' residential locations over time. To assess this, I estimate a difference-in-differences event-study specification that compares the characteristics of households moving into low-opportunity neighborhoods in Dallas to those moving into similar neighborhoods in control metros. I identify all such movers and associate each household i with the neighborhood j it moves to in each year t. I estimate the following

$$Y_{it} = \alpha_j + \alpha_t + \sum_{\tau} \beta_\tau \times \mathbb{I}_{jt}[t - t^* = \tau, m(j) = 1] + \varepsilon_{it} \quad (4)$$

where Y_{it} are the household's demographic characteristics including income and race. α_j and α_t are ZIP code and year fixed effects, respectively.

A key challenge is that household income and race variables in InfoUSA are imputed by the data provider and are therefore subject to measurement error. To address this concern, I follow Asquith et al. (2023) and proxy household characteristics using the demographic attributes of the neighborhoods from which households originate. Specifically, I use the median household income and racial composition of the origin ZIP code as measures of households' economic and demographic characteristics prior to moving.

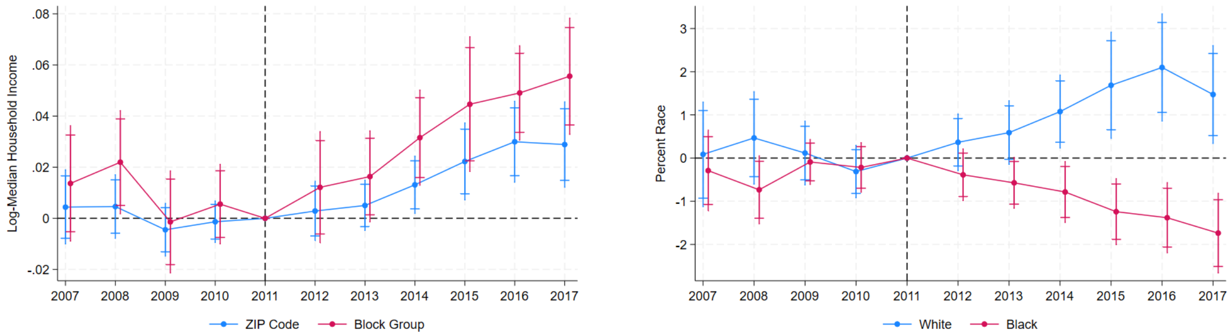
The left panel of Figure 6 presents event-study estimates for the median household income of origin neighborhoods for households moving into low-opportunity neighborhoods. Results are shown using both ZIP code-level and Census block group-level origin characteristics. In the pre-treatment period, the estimates are flat and statistically insignificant between Dallas and control metros, supporting the parallel trend assumption. However, following SAFMR adoption, there is a clear and gradual increase in the income of origin neighborhoods for in-migrants to low-opportunity areas. By 2017, households moving into low-opportunity neighborhoods originated from ZIP codes with approximately 3 percent higher median household income. When using block group-level measures, which should better capture socioeconomic characteristics of in-migrants, the effect is larger at around 6 percent.

These patterns indicate that households moving into low-opportunity neighborhoods after SAFMR have systematically higher income than earlier in-migrants. This finding is consistent

Figure 6: Characteristics of In-Migrants to Low-Opportunity Neighborhoods

(a) Origin Neighborhood's Median HH Income

(b) Origin Neighborhood's Racial Composition



Notes: The figures above plot the event-study coefficients of the effect of SAFMR on in-migration patterns to low-opportunity neighborhoods. In the left panel, the dependent variable is the log median household income of a neighborhood (either zip code or block group) an in-migrant originated from. The dependent variable in the right panel is the share of the respective race group of a zip code an in-migrant originated from. 95 percent confidence intervals are shown in the figures. The standard errors are clustered at the zip code level.

with the aggregate results in low-opportunity neighborhoods shown in Section 5.3 which show rising shares of middle-income households in low-opportunity areas following the policy. Both micro and aggregate evidence point to a re-sorting of non-voucher, middle-income households toward lower-rent areas as rents and demographic composition change in higher-opportunity areas.

The right panel of the same figure reports analogous results for racial composition, focusing on the share of White and Black residents in origin neighborhoods. After SAFMR, in-migrants to low-opportunity neighborhoods originate from ZIP codes with, on average, higher White population share and lower Black population share. Again, these patterns closely align with the aggregate changes at different demographic margins as shown earlier.

I present analogous migration analyses for in-migrants to high- and mid-opportunity neighborhoods in Appendix Section C. These estimates should be interpreted with caution, however, as InfoUSA tends to under-represent low-income and non-White households, precisely the groups most likely to move into higher-opportunity neighborhoods following SAFMR. Therefore, the migration responses documented here are most informative about the re-sorting behavior of unsubsidized, middle-income households, which is the margin of interest for understanding equilibrium responses and welfare incidence which is discussed in Section 7.

5.4.2 Relocation within High-Opportunity Neighborhoods

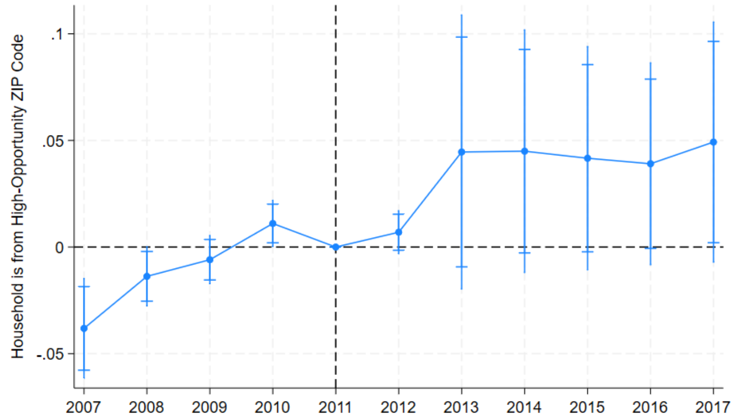
The aggregate analysis shows little change in the share of households earning more than $100,000 in high-opportunity neighborhoods. There are two plausible interpretations of this result. First, high-income households may not respond to the policy and simply remain in their original locations. Second, incumbent high-income households in high-opportunity neighborhoods may respond by relocating to other high-opportunity neighborhoods that experienced relatively smaller inflows of voucher households. The latter involves high-income households actually moving actively, but these moves would not be reflected in aggregate neighborhood composition measure because both origin and destination neighborhoods are classified as high-opportunity.

To distinguish between these two explanations, I run the migration analysis using as the outcome an indicator for whether an in-migrant to a high-opportunity neighborhood originated from another high-opportunity neighborhood. This directly tests whether internal relocation within the set of high-opportunity neighborhoods increased following SAFMR.

Figure 7 presents the event-study estimates. Although weakly significant, the coefficients show increases in internal migration among high-opportunity neighborhoods. The share of in-migrants to high-opportunity neighborhoods who originate from other high-opportunity areas increased by approximately 5 percentage points.

This evidence supports the second interpretation of the aggregate null result. Rather than remaining completely unresponsive, some high-income households appear to re-optimize their residential choices by relocating across high-opportunity neighborhoods. One plausible mechanism is that the inflow of voucher households made certain high-opportunity neighborhoods less attractive to incumbent high-income households, incentivizing them to move to other high-opportunity neighborhoods that experienced smaller or no voucher inflows.

Figure 7: Households Moving from High-Opportunity to High-Opportunity Neighborhoods



Notes: The figure above plots the event-study coefficients of the effect of SAFMR on in-migration patterns to high-opportunity neighborhoods. The dependent variable is an indicator for whether an in-migrant originated from a high-opportunity zip code. 95% confidence intervals are shown. The standard errors are clustered at the zip code level.

6 A Model of Neighborhood Choice

The introduction of SAFMR affects neighborhoods and the rental market through combined residential decisions made by both voucher and non-voucher households in equilibrium. As discussed in Section 5.2, the price responses are heterogeneous across neighborhoods depending on the attractiveness of neighborhoods to voucher households. Voucher households' relocations trigger rent price changes through demand effect and compositional effect channels in equilibrium. In this section, I develop and estimate a model of equilibrium residential sorting based on Almagro et al. (2023) to further study the channels driving changes in rent prices and demographic compositions across neighborhoods after policy implementation.

I first classify households into different income groups n. Each household in group n chooses its residential location by solving the following maximization problem:

$$\max_j V_{ijt}^n = \delta_{jt}^n + \varepsilon_{ijt}^n$$

The indirect utility is a function of two entities. First is a common utility component δ_{jt}^n that is specific to each group and parameterized as

$$\delta^n_{jt} = \alpha^n_P \ln P_{jt} + \alpha^n_L L_{jt} + \alpha^n_X X_{jt} + \xi^n_{jt}$$

where P_{jt} is the rent price of each Census tract j in year t (as measured by the median gross rent) and L_{jt} is the share of poor households (as measured by households in the first income-quartile group). Note that this share is inclusive of both voucher households and non-voucher households in the first income-quartile group. They are the two endogenous features in the model that will respond to the policy in equilibrium. X_{jt} is a vector of exogenous neighborhood characteristics, including the share of owner-occupied housing, the log of the median number of rooms, the share of workers who commute with public transportation, the share of housing stocks that are built after 2010, and the share of buildings with more than 50 units, and ξ^n_{jt} is a scalar that summarizes unobservable neighborhood characteristics. The remaining component, ε^n_{ijt}, is an idiosyncratic shock each household i receives for living in neighborhood j in year t and is assumed to be drawn from an i.i.d. Extreme Value Type 1 distribution (EVT1). I allow household's preference parameters $\alpha^n = (\alpha^n_P, \alpha^n_L, \alpha^n_X)$ to be group specific.

Given the distributional assumption on ε^n_{ijt}, the choice probability of household group n living in neighborhood j in year t can be written as

$$\sigma^n_{jt}(\mathbf{P}_t, \mathbf{L}_t, \mathbf{X}_t, \xi^n_t; \alpha^n) = \frac{\exp\{\delta^n_{jt}\}}{\sum_{j'} \exp\{\delta^n_{j't}\}}$$

where $\mathbf{P}_t$, $\mathbf{L}_t$, and $\mathbf{X}_t$ represent vectors of P_{jt}, L_{jt}, and X_{jt}, respectively, across all neighborhoods in each year. Similarly, ξ^n_t is a group-specific vector of the unobserved component of the utility across all neighborhoods. Using the above form of choice probabilities, the total demand for neighborhood j in year t follows as

$$\mathcal{D}_{jt}(\mathbf{P}_t, \mathbf{L}_t, \mathbf{X}_t, \xi_t; \alpha) = \sum_n \sigma^n_{jt}(\mathbf{P}_t, \mathbf{L}_t, \mathbf{X}_t, \xi^n_t; \alpha^n)\, N^n_t$$

where N_t^n is the total number of households in group n. I take this as an exogenously given number.

I assume there is an isoelastic curve that governs the housing supply for each neighborhood as follows

$$\mathcal{S}_{jt}(P_{jt}) = \theta_{jt} P_{jt}^{\psi}$$

where θ_{jt} is the supply shifter and ψ a measure of housing supply elasticity. The intercept will be calibrated later using the elasticity measure for Dallas borrowed from other literature.

Using the model components above, I define that the model has achieved an equilibrium when the rent price and share of poor households in each neighborhood clear the market. More specifically, the equilibrium occurs when the endogenous vectors of rent price and share of poor households, $\mathbf{P}_t^*$ and $\mathbf{L}_t^*$ respectively, solve the following system of equations

$$\begin{cases} \mathcal{D}_{jt}(\mathbf{P}_t^*, \mathbf{L}_t^*, \mathbf{X}_t, \xi_t; \alpha) = \mathcal{S}_{jt}(P_{jt}^*) & \forall j = 1, \dots, J \\ \frac{\mathcal{D}_{jt}^L(\mathbf{P}_t^*, \mathbf{L}_t^*, \mathbf{X}_t, \xi_t; \alpha)}{\mathcal{D}_{jt}(\mathbf{P}_t^*, \mathbf{L}_t^*, \mathbf{X}_t, \xi_t; \alpha)} = L_{jt}^* & \forall j = 1, \dots, J \end{cases}$$

where $\mathcal{D}_{jt}^L(\cdot)$ represents the equilibrium number of poor household living in neighborhood j. The first condition indicates that the demand for housing is equal to the supply in all neighborhoods. The second condition is satisfied when the model-implied share of poor households equals the guess of the share used in the model simulation.

6.1 Estimation of Preference Parameters

For estimation of preference parameters, I quantify the model based on Berry (1994). I first take living in the Fort Worth part of the metropolitan area as the model's outside option. Fort Worth metro is located right next to the Dallas metro and shares a border on its right side, making it the perfect outside option to quantify the model. I index living in Fort Worth as $j = 0$ and normalize the utility of living there as 0 (i.e. $\delta_{0t}^n = 0$). This normalization then implies the following relationship that can be taken directly to aggregate data for the estimation of the preference parameters:

$$\ln\left(\frac{\sigma^n_{jt}}{\sigma^n_{0t}}\right) = \alpha^n_P \ln P_{jt} + \alpha^n_L L_{jt} + \alpha^n_X X_{jt} + \xi^n_{jt} \tag{5}$$

where the choice probabilities (i.e. σ's) will be estimated using the share of households of group n living in neighborhood j from the ACS data. More specifically, the estimated shares follow as

$$s^n_{jt} = \frac{\text{Number of households of group } n \text{ living in neighborhood } j \text{ in year } t}{\text{Number of households of group } n \text{ living in the Dallas-Fort Worth metro in year } t}$$

One empirical challenge in this estimation procedure is that there are neighborhoods where there is 0 or 1 share of a particular income group because the ACS data is based on a small sample of survey respondents. Such shares are inconsistent with the distributional assumption on ε^n_{ij} and exclude a handful of neighborhoods out of the households' consideration set which is unrealistic. Thus, I smooth out the choice probabilities by taking a distant-weighted average of the frequency estimates across Census tracts as follows

$$\tilde{s}^n_{jt} = \sum_{k \in \mathcal{J}_j} w_{jk} s^n_{jt}$$

where $\mathcal{J}_j$ is a set of Census tracts whose geographic centroids are within 20 miles away from tract j and each of the weights is calculated as

$$w_{jk} = \left(\frac{1}{1 + \text{dist}(j, k)}\right)^5 \Big/ \left(\sum_{k' \in \mathcal{J}_j} \frac{1}{1 + \text{dist}(j, k')}\right)^5$$

which total to 1 for each tract j.[29]

With the arsenals above, I estimate a version of Equation (5) using repeated cross-sections from

[29] I take the fifth-power for the weight calculation for better approximation to shares of 0 and 1.

two 5-year ACS from 2006-2010 and 2015-2019 ACS as follows

$$\ln\left(\frac{\tilde{s}^n_{jt}}{\tilde{s}^n_{0t}}\right) = \alpha^n_P \ln P_{jt} + \alpha^n_L L_{jt} + \alpha^n_X X_{jt} + \lambda^n_j + \lambda^n_t + \tilde{\xi}^n_{jt}$$

where I include group-specific Census tract fixed effects, λ^n_j, to account for time-invariant characteristics of neighborhoods and year fixed effects, λ^n_t, to control for common shocks in Dallas throughout two time periods.

However, there is another concern in estimation. It is immediately obvious that a simple OLS of the above will return biased coefficients as rent prices are likely to be correlated with the unobserved attributes of the neighborhoods, $\tilde{\xi}^n_{jt}$. To address this issue, I use two sets of instruments. First, I construct instruments based on standard practice in the urban economics literature following Bayer et al. (2007). I calculate separate averages of exogenous characteristics of neighborhoods whose centroids are 20 to 30 miles away including the shares of housing units with 2 bedrooms, shares of buildings with 1 unit and 50 or more units, separately, and shares of housing units built pre-1970 and post-2000, separately.[30] These instruments are based on the idea of the seminal work of Berry et al. (1995) where Census tracts are considered as competing products in an area and their characteristics indirectly affect other tracts' housing prices and demographic compositions through an equilibrium process.

The other instrument comes from the policy itself: the number of voucher-eligible rental units in each neighborhood. Newly assigned neighborhood-level FMRs opened up a substantial part of the rental units to voucher households in higher-opportunity neighborhoods, whereas it had the opposite effect in lower-opportunity neighborhoods. Thus, this policy instrument is a great instrument for demographic composition in particular. The new level of FMRs is directly related to how eligible rental units are for voucher households. The relevance condition is satisfied as changing levels of the FMRs determine the availability of rental units to voucher households. A positive change in the FMR opens up a substantial number of units for voucher households which are potentially related

[30] I find from first-stage analysis and confirm that characteristics of neighborhoods that are 20-30 miles away have a significant impact on rent prices and demographic characteristics through the equilibrium process in Dallas.

to the increasing number of poor households in the neighborhood. A negative change in the value, on the other hand, is associated with a decrease in the share of the poor population. This fact is well established in the empirical analysis in Section 5.3. Such movements of the voucher households are the channels through which it affects neighborhood compositions and rent prices coming from both demand and compositional effects. This policy instrument also satisfies the exclusion restriction as the policy was instituted in an unexpected manner following a lawsuit, suddenly changing the eligibility of rental units to voucher households.[31]

In estimation, I categorize households into four groups by income quartiles for each year based on household income distribution in the Dallas-Fort Worth metropolitan area. The first income-quartile group includes households earning less than \$30,000 and \$40,000 in 2010 and 2019, respectively; the second income-quartile group includes households earning between \$30,000 and \$60,000 in 2010 and between \$40,000 and \$75,000 in 2019; the third income-quartile group includes households earning between \$60,000 and \$100,000 in 2010 and \$75,000 and \$125,000 in 2019; and the fourth income-quartile includes households earning more than \$100,000 and \$125,000 in 2010 and 2019, respectively.[32,33] To account for the number of voucher households in each neighborhood, I subtract the number of them from the total number of households in the first income quartile living in each tract.[34]

Table 3 presents the coefficients for preference parameters for each income group.[35] The first row captures each group's quantified preference for paying more for housing. All across the board,

[31] Note that a one-time change in the number of voucher eligible units in 2011 is used as the instrument. That is, I use the number of voucher-eligible units under the metro-level FMR in 2011 as an instrument for the 2006-2010 ACS, whereas I use the number of voucher-eligible units under SAFMR in 2011 as an instrument for the 2015-2019 ACS. This is to avoid the potential endogeneity between the instrument and the rent prices; the changes in rent prices may also change the FMR values in 2019.

[32] The more granular binning of income groups is less desirable with the current data at hand as having finer income groups lead to less precise estimates of preference parameters.

[33] Another possible estimation strategy is to utilize the household-level microdata (e.g. InfoUSA) as is typically done in other residential sorting literature. However, the InfoUSA data is not suitable for examining the location patterns of *low-income* households in particular. The data in general does a poor job of capturing non-white and low-income households. This is critical in my research setting as the changes in residential equilibrium are catalyzed by the movements of low-income households.

[34] In rare occasions, some tracts end up having a negative number of first income-quartile households when the number of voucher households is accounted for. I simply replace the negative counts with 0 in a handful of such cases.

[35] I provide summary statistics of different demographic groups for the 2015-2019 ACS in Appendix C.

Table 3: Estimates of Neighborhood Preference Parameters for Non-Voucher Households (IV)

	Income Group			
	Q1	Q2	Q3	Q4
Log(Median Gross Rent)	-2.350***	-2.832***	-1.516**	-1.527*
	(0.883)	(0.882)	(0.766)	(0.809)
Share Poor	-1.094	-4.166	-6.486***	-4.578*
	(2.627)	(2.624)	(2.278)	(2.404)
Tract Fixed Effects	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y
Additional Controls	Y	Y	Y	Y
Number of Tracts	890	890	890	890
Observations	1780	1780	1780	1780

Notes: This table presents instrumental variable regression results of preference parameters for endogenous neighborhood attributes including median gross rent and share of poor households as defined by those in the first quartile income group (Q1). Exogenous neighborhood characteristics include share of owner-occupied housing units, share of workers commuting with public transportation, median number of rooms, median year of buildings built, share of buildings with 1 unit, and share of buildings with more than 50 units.

the coefficients are negative and statistically significant as expected: households in all income groups do not like paying more rent. The second row reveals each group's preference toward having poor households as their neighbors. All non-voucher households have negative preferences for having low-income households in their neighborhoods. The two estimates find that households in the first income-quartile group are willing to pay $103 more towards their annual rent payments to reduce the number of low-income neighbors by one percentage point, whereas higher-income groups have a much higher willingness to pay to avoid having to live near poor neighbors.

It is important to clarify the interpretation of these estimates. The negative coefficients on the share of low-income households should not be read as evidence of animosity or distaste toward poor neighbors per se. Rather, they capture households' reduced utility from a bundle of neighborhood attributes that are correlated with poverty concentration but are not directly observed in the data. These attributes may include school quality, public goods provision, local amenities—all of which tend to co-vary with neighborhood income composition in equilibrium. As a result, the estimated coefficients reflect preferences over neighborhoods as composite bundles rather than direct preferences over the income of neighbors.

The derived preference estimates resonate strongly with the underlying mechanisms through which the rent prices and demographic compositions change across different neighborhoods in Dallas. The previous empirical results suggest a pronounced tendency among voucher households to gravitate toward neighborhoods with high minority shares (which coincides with shares of poor households in the context of the model). Given high-income households' high willingness-to-pay to avoid poor neighbors and a surge of voucher households to a handful of high-opportunity neighborhoods, these non-voucher high-income households are likely to relocate and seek residence in other high-opportunity neighborhoods where the number of voucher households remains low. Thus, the price increase in high-opportunity neighborhoods documented in the empirical section can be attributed to the increase in demand from these high-income households moving away from voucher households. However, the overarching price effects will somewhat be muted due to the disamenities caused by the influx of voucher households to a few of these high-opportunity neighborhoods.

7 Welfare Impact on Non-Voucher Households

In this section, I study the welfare impact of SAFMR on non-voucher households. By raising effective rents in high-opportunity neighborhoods, the policy made it more costly for non-voucher households to access or remain in those neighborhoods relative to the pre-policy environment. To quantify these welfare effects, I compare two simulated residential equilibria in 2019: one under SAFMR and one under the counterfactual metropolitan-level FMR design.

Given that neighborhood choice model is estimated using neighborhood *rent* prices, I assume that renters and homeowners within a given income group share the same preferences. I further assume that home prices equal the present discounted value of rents. Under these assumptions, homeowners and renters within the same income group make identical locational choices.

The foundation of the welfare analysis will be the comparison of the counterfactual equilibrium

$(\mathbf{P}^1, \mathbf{L}^1, \mathbf{X}^1)$ relative to the baseline equilibrium $(\mathbf{P}^0, \mathbf{L}^0, \mathbf{X}^0)$ to derive welfare gain/loss in monetary terms. To do so, I first establish a notion of rent equivalence, RE^n, the rent increase necessary to leave the households indifferent in the counterfactual scenario with respect to the baseline scenario. More specifically, the rent equivalence is defined as

$$\mathcal{CS}^n(\mathbf{P}^1 + RE^n, \mathbf{L}^1, \mathbf{X}, \xi^n; \alpha^n) = \mathcal{CS}^n(\mathbf{P}^0, \mathbf{L}^0, \mathbf{X}, \xi^n; \alpha^n)$$

where $\mathcal{CS}^n(\cdot)$ is the average consumer welfare of households of income group n. Following the assumed error structure in the model, it can be written in a closed form as

$$\mathcal{CS}^n(\mathbf{P}, \mathbf{L}, \mathbf{X}, \xi^n; \alpha^n) = \ln\left(\sum_j \exp\left\{v^n_{jt}(\mathbf{P}, \mathbf{L}, \mathbf{X}, \xi^n; \alpha^n)\right\}\right)$$

The households have welfare *gain* for a particular income group if the associated value of rent equivalence is positive.

Focusing exclusively on rent equivalence measure, however, would provide an incomplete picture of welfare impacts in Dallas, where 58 percent of occupied housing units were owner-occupied in 2019 as shown in Table 1. To account for this, I assume that homeowners receive a flow of rental income from their housing portfolio. Thus, the total welfare effects of income group n are defined as the sum below:

$$RE^n + \sum_j s_j^{n,\text{own}} \Delta P_j \tag{6}$$

where $s_j^{n,\text{own}}$ is the share of homeowners of income group n is neighborhood j and ΔP_j is the change in rent in neighborhood j between the counterfactual and baseline scenarios.[36]

[36] In NHGIS, the income bins defined by tenure status do not align perfectly with the income bins defined for the number of households living in each neighborhood in each income bin. Thus, the income range of each income quartile differs slightly from the definitions used above: for 2019, the first income quartile is defined as households earning less than \$35,000, the second is defined as households earning between \$35,000 and \$75,000, the third is defined as households earning between \$75,000 and \$150,000, and the fourth is defined as households earning more than \$150,000.

7.1 Welfare Impact from Small Area Fair Market Rents

I first quantify the welfare effects of SAFMR on non-voucher households by computing the average change in welfare for each income group induced by the policy. This exercise requires simulating a counterfactual residential equilibrium under MFMR design using the parameters estimated in the neighborhood choice model.

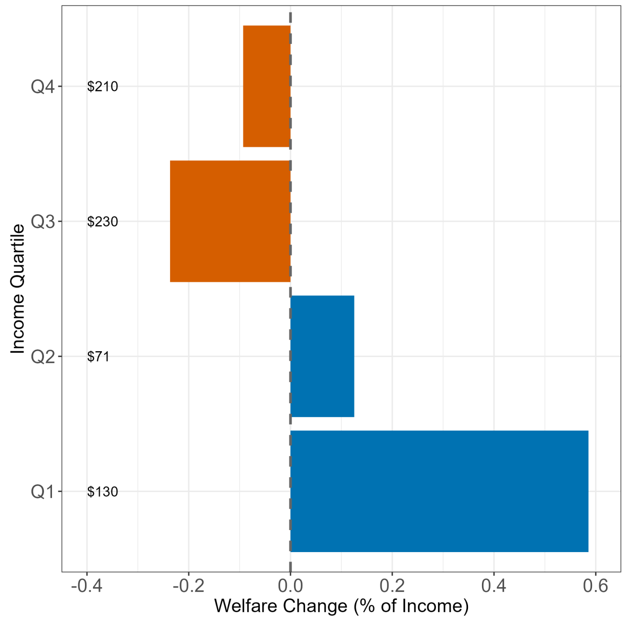
A key challenge, however, is that I do not explicitly model the residential choice behavior of *voucher* households. Modeling voucher households' location decisions would require incorporating a substantially more complex optimization problem shaped by binding payment standards, landlords' willingness to take voucher tenants, search frictions, and various forms of discrimination.[37] The aggregate nature of the PoSH data limits the feasibility of estimating a fully structural neighborhood choice model of voucher households.

Since I cannot allow voucher households to self-sort in the model, I must take a stance on where voucher households would have been located in 2019 in the absence of SAFMR, treating their locations as exogenously given in the welfare simulations. To construct a plausible MFMR counterfactual, I assume that the spatial distribution of voucher households across neighborhoods in 2019 would have remained the same as in 2010. To put this more concretely, I fix the *share* of voucher households in each neighborhood at its 2010 level and scale this distribution to match the total number of voucher households observed in Dallas in 2019 when simulating the MFMR equilibrium. The rationale behind this simplification is to approximate a counterfactual equilibrium in which voucher households in 2019 face constraints similar to those prevailing before the policy was introduced. While this simplification comes with limitations and abstracts from endogenous relocation by voucher households, it provides the most probably approximation of their likely spatial distribution under a continued MFMR regime.

I compare the simulated MFMR equilibrium to the one observed in 2019 under SAFMR and

[37]A significant portion of voucher households comprises minority groups, making them susceptible to racial discrimination in the rental market (Christensen et al., 2021; Christensen and Timmins, 2022, 2023). Beyond racial bias, these households also confront discrimination based on income and voucher status. Such biases have been exacerbated in Texas, where a 2015 law was enacted to shield landlords from repercussions for discriminating against voucher families. Other friction includes high housing search costs for low-income families (Bergman et al., 2024).

Figure 8: Welfare Impacts of SAFMR



Notes: The figure above summarizes the impact of SAFMR on each non-voucher income group's welfare. The welfare measures are given in shares of the average yearly income of each income group. The dollar values of the welfare changes are listed on the left side of the figure.

report the resulting welfare impacts in Figure 8.[38] The results indicate that SAFMR reduced welfare for high-income non-voucher households while increasing welfare for lower-income non-voucher households. Households in the third and fourth income quartiles experienced annual welfare losses of approximately $230 and $210, corresponding to about 0.2 and 0.1 percent of their annual income, respectively. These losses reflect higher effective rents in high-opportunity neighborhoods and increased presence of low-income neighbors.

In contrast, non-voucher households in the lower part of the income distribution (indirectly) benefited from this change in equilibrium. Households in the first income quartile, in particular, experienced substantial welfare gains equivalent to roughly 0.6 percent of their annual income, driven by lower market rents and increased presence of higher-income neighbors in low-opportunity neighborhoods. Unsubsidized households in the second income quartile also experienced positive welfare effects, though of smaller magnitude.

[38]For internal consistency, I also simulate a baseline equilibrium using observed neighborhood characteristics and estimated fixed effects. The model shows a good fit and is shown in Appendix B.

Table 4: Welfare Decomposition into Separate Equilibrium Channels

	ΔWelfare from MFMR baseline in share of RE			
	Q1	Q2	Q3	Q4
Change only rent price	0.54	0.89	-0.44	-0.84
Change only share poor	0.46	0.11	-0.56	-0.16

Notes: The table above shows the quantitative importance of the equilibrium channels contributing to the welfare gain/loss for each unsubsidized income group. The first row highlights the share of rent equivalent measure of welfare that is gained (or lost) due to changes in rent prices across neighborhoods. The second row highlights the share of welfare change due to changes in the share of first income-quartile households across neighborhoods.

Overall, these results indicate that SAFMR is a much more progressive design of HCV than the traditional system with metropolitan-level FMR system. Beyond directly expanding access to high-opportunity neighborhoods for voucher households through higher subsidies, SAFMR indirectly benefits unsubsidized low-income households by lowering market rents in lower-opportunity neighborhoods and changing demographic composition through equilibrium spillovers. However, higher-income non-voucher households bear modest welfare losses resulting from increased competition and higher prices in high-opportunity neighborhoods as well as the neighborhood composition changes.

Decomposition Analysis

In this section, I decompose the welfare effects of SAFMR to quantify the relative importance of the two endogenous equilibrium channels: (1) changes in rent prices and (2) changes in neighborhood demographic composition. To do so, I conduct a sequence of counterfactual simulations in which I allow only one channel to adjust at a time while holding the other fixed at its baseline level. Then, I compute the implied rent-equivalent welfare measure for each income group. This exercise isolates the contribution of each channel to the total welfare change induced by SAFMR, and the results are reported in Table 4.

The first row of the table reports the share of the total welfare change attributable solely to changes in neighborhood rent prices, holding demographic composition fixed. The second row reports the corresponding share attributable to changes in neighborhood composition measured by the share of low-income households, holding rents fixed.

For non-voucher households in the lowest income quartile (Q1), welfare gains arise almost equally from both channels. About half of the total welfare gain is driven by lower rents in low-opportunity neighborhoods, while the remaining half reflects changes in neighborhood composition, specifically greater exposure to higher-income neighbors relative to the pre-SAFMR equilibrium. This suggests that for the poorest unsubsidized households, both affordability improvements and compositional changes play equal role in boosting their welfare.

The welfare decomposition for Q1 households closely reflects the relocation margins documented in the earlier empirical sections. The roughly equal contribution of rent and compositional channels is consistent with the pronounced de-concentration of poverty through voucher households' relocation in low-opportunity neighborhoods. These households benefit from lower rents as voucher households exit the neighborhoods where the poorest non-voucher households are most likely to reside, while simultaneously experiencing improvements in neighborhood composition as some higher-income households relocate into these areas.

For households in the second income quartile (Q2), welfare gains are overwhelmingly driven by the rent channel which accounts for nearly 90 percent of the total effect. These households benefit primarily from access to lower-priced housing in neighborhoods that become more affordable following SAFMR-induced re-sorting, with comparatively little contribution from changes in neighborhood composition.

On the other hand, welfare losses among higher-income households operate through different channels. For households in the top income quartile (Q4), the welfare loss is driven almost entirely by higher rents. It accounts for about 84 percent of the total loss. This pattern, again, is consistent with the relocation patterns from before. They respond to SAFMR by relocating within the set of high-opportunity neighborhoods and paying higher prices to avoid neighborhoods experiencing large voucher inflows.

For unsubsidized households in the third income quartile (Q3), welfare losses are more evenly split across the two channels. These households are sufficiently price-sensitive that rising rents in high-opportunity neighborhoods induce them to move down the opportunity ladder, resulting in both higher effective housing costs and greater exposure to lower-income neighbors. Thus, both rent increases and compositional changes contribute to their welfare losses.

7.2 Welfare Impact from Housing Choice Voucher Program

In the previous section, I quantified how replacing metro-level FMRs with ZIP code-level ones alters welfare among non-voucher households. However, it is equally important to understand the welfare consequences of HCV program itself, independent of how payment standards are designed.

To do so, I simulate two additional counterfactual equilibria using the estimated model. First, I evaluate the welfare impact of introducing the voucher program under the traditional metro-level FMR design. Starting from an environment without vouchers, I allow voucher households to enter the market and self-sort using the estimated preferences of the lowest income quartile.[39] Comparing this equilibrium to the no-voucher baseline captures the welfare effect of implementing HCV with a metro-wide payment standard. Second, I conduct an analogous exercise for SAFMR. I remove the voucher program from the world with SAFMR and then simulate the equilibrium that comes about when vouchers are introduced under ZIP code-level payment standards.[40] Together, these two exercises allow me to compare how the welfare incidence of the voucher program across unsubsidized households differs under MFMR versus SAFMR.

Figure 9 summarizes the results for both scenarios. The left panel shows the welfare effects of introducing MFMR relative to a world without vouchers. With the exception of the highest-income group, all non-voucher households experience welfare losses. The burden is especially large for the lowest-income quartile, while experiences an average welfare loss equivalent to about 3 percent of annual income. The right panel shows the welfare effects of introducing SAFMR relative to a no-voucher counterfactual world. Welfare losses for the second through fourth income quartile is

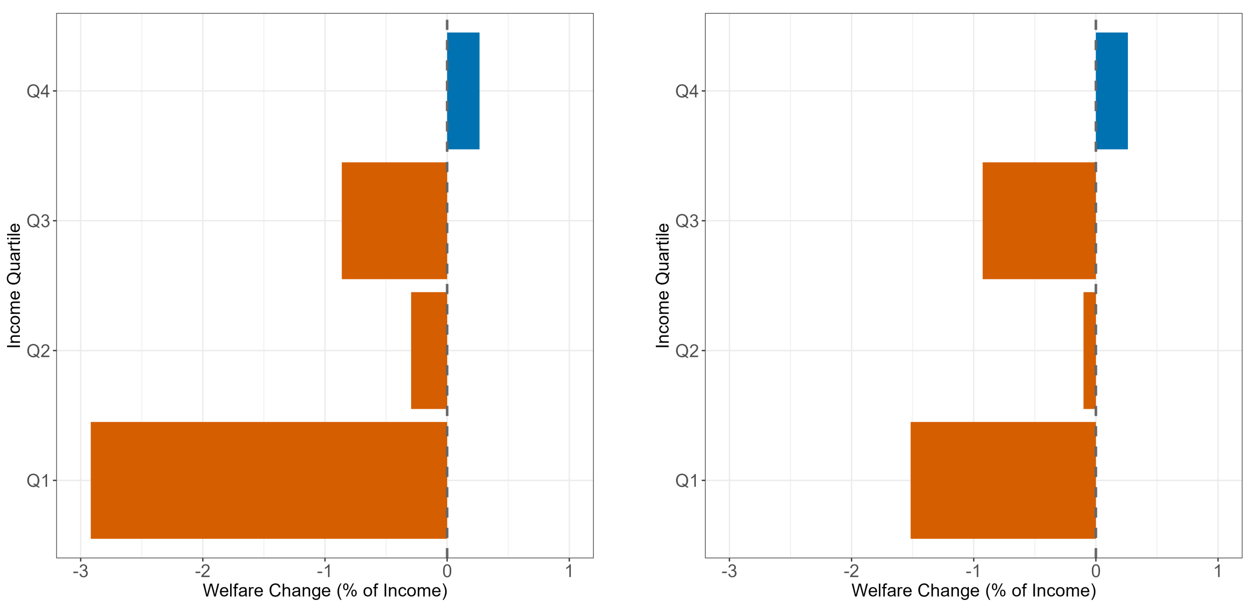
[39] Note that this simulation is based on 2010, prior to SAFMR adoption.

[40] Note that this simulation is based on 2019 after SAFMR had been in place for a few years in Dallas.

still are still present as in the MFMR case. However, the welfare loss for low-income households are significantly lower. In particular, the welfare loss for the lowest-income quartile fell to about 1.5 percent of annual income. The results suggest that although SAFMR does not eliminate the negative welfare effects of the voucher program to non-recipients, it significantly reduces the welfare burden borne by the poorest unsubsidized households.

Figure 9: Welfare Impacts of Housing Choice Voucher Program by FMR Designs

(a) No Voucher → MFMR (b) No Voucher → SAFMR



Notes: The figures above summarize the impact of implementing the respective version of the HCVP in a world without HCVP on each non-voucher income group's welfare. The left panel depicts the welfare impact of instituting MFMR, whereas the right panel presents the welfare impact of instituting SAFMR. The welfare measures are given in shares of the average yearly income of each income group.

The concentration of welfare losses among low-income non-voucher households under both MFMR and SAFMR designs reflects a fundamental feature of the voucher program. Vouchers inevitably injects demand into the rental market pushing up market prices (Susin, 2002). By design, this demand is disproportionately concentrated in low-opportunity neighborhoods under a metropolitan-level payment standard. Increased demand for rental units in these areas raises market rents and more likely to disproportionately harm unsubsidized households who live in these neighborhoods.

However, SAFMR partially mitigates this mechanism by redirecting some voucher demand toward higher-opportunity neighborhoods. By expanding voucher eligibility in high-rent areas and contracting it in low-rent areas, it reduces demand pressure in the neighborhoods where unsubsidized low-income households are most likely to live. As a result, the welfare losses associated with the voucher program are spread more evenly across the income distribution rather than being concentrated almost entirely on the poorest non-recipients.

Taken together, the results in this section and Section 7.1 highlight two competing forces inherent in running the voucher program. On one hand, the program improves access to housing for a subset of low-income households who receive vouchers. On the other hand, it imposes nontrivial welfare costs on low-income households who do not receive assistance. Conditional on implementing a voucher program, however, SAFMR emerges as a more equitable design as it preserves the benefits to voucher recipients while substantially reducing the welfare burden imposed on unsubsidized low-income households and redistributing that burden toward higher-income groups.[41]

7.3 Welfare Impact under Alternative Housing Supply Elasticities

It is important to move beyond the Dallas case and consider how the welfare implications of voucher and its design may vary across markets, particularly because HUD extended SAFMR to many metropolitan areas in 2018 and again in 2025, with further expansions likely going forward. A key dimension along with metros differ is housing supply elasticity. For example, among the metros mandated to adopt SAFMR, Chicago and Charlotte have estimated supply elasticities of 0.19 and 0.46, respectively, according to estimates from Baum-Snow and Han (2024). These differences motivate an assessment of how the welfare impacts of voucher design may vary under alternative housing supply conditions.

To examine this, I simulate counterfactual equilibria under alternative supply elasticities (i.e., vary ψ in housing supply function calibration). Intuitively, higher supply elasticity may dampen price responses to demand shocks. When housing supply can respond more easily, increases in

[41] Directly comparing welfare changes for voucher and non-voucher households is beyond the scope of this paper as I do not explicitly model voucher households' residential choice problem.

voucher demand in high-opportunity neighborhoods may translate into little or no rent increases, and reductions in demand in low-opportunity neighborhoods may lead to smaller rent declines. As a result, one would expect welfare effects to be attenuated as supply becomes more elastic, particularly for households whose welfare changes are driven primarily by rent movements.

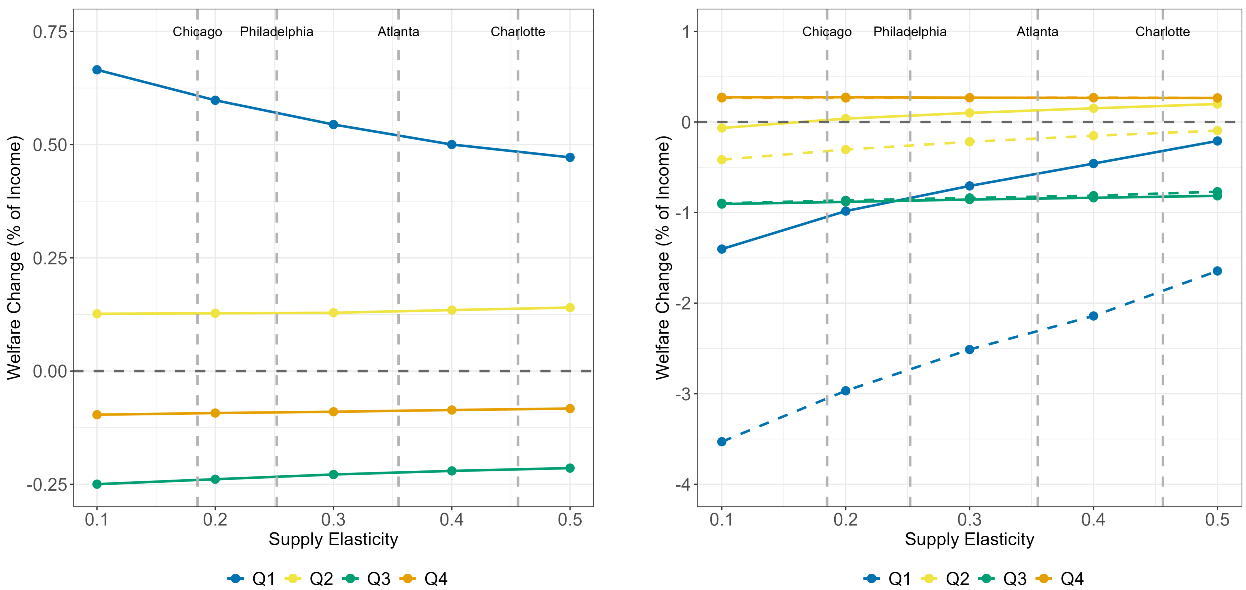
Figure 10 summarizes the welfare effects under alternative housing supply elasticities. The left panel shows the welfare impact of moving from MFMR to SAFMR expressed as a share of each income group's annual income like before. For Q2 through Q4 non-voucher households, welfare effects are small to begin with (as in Figure 8), and varying supply elasticity has little effect on their magnitude. However, the welfare gains experienced by the lowest-income non-voucher households are strongly sensitive to supply elasticity. When supply is relatively inelastic, SAFMR generates larger rent declines in low-opportunity neighborhoods, leading to greater welfare gains for this group. As supply becomes more elastic, these rent deductions are potentially muted so the associated welfare gains diminish accordingly.

The right panel of the figure presents the welfare effects of introducing the voucher program itself to a world without HCV. Dashed lines show the welfare impact of instituting MFMR, while solid lines show the impact of instituting SAFMR. Once again, supply elasticity plays a limited role for higher-income non-voucher households. On the other hand, the welfare losses experienced by the lowest-income non-voucher households are highly sensitive to supply elasticity. When housing supply is elastic, these price pressures weaken and the welfare losses shrink substantially under both MFMR and SAFMR, though MFMR consistently imposes a larger burden.

In summary, housing supply elasticity matters in shaping the welfare consequences of voucher policies, with particularly pronounced effects for the lowest-income non-voucher households. In markets with inelastic housing supply, voucher programs generate larger rent spillovers and more pronounced welfare redistribution, making program design especially consequential. In more elastic markets, price responses are muted and welfare effects are correspondingly smaller. These findings highlight the importance of accounting for local housing supply conditions when designing or reforming voucher programs, particularly given that the largest welfare impacts fall on the same

Figure 10: Welfare Impacts under Alternative Housing Supply Elasticities

(a) MFMR → SAFMR (b) No HCVP → MFMR or SAFMR



Notes: The figures above summarize the impact of various versions of implementing the voucher programs on each non-voucher income group's welfare under various housing supply elasticities. The left panel illustrates the welfare impact of instituting SAFMR to a world with MFMR. The right panel illustrates the welfare impact of instituting either MFMR or SAFMR to a world without HCVP. In the right panel, the dashed lines represent the welfare estimates of implementing MFMR, whereas the solid lines represent the welfare estimates of implementing SAFMR. The welfare measures are given in shares of the average yearly income of each income group. The vertical dashed lines represent the housing supply elasticity measures for respective metropolitan areas given in Baum-Snow and Han (2024).

low-income populations the program is intended to support.

8 Conclusion

This paper studies the equilibrium effects of Small Area Fair Market Rents (SAFMR), a redesign of the largest federally administered tenant-based housing assistance program in the United States, the Housing Choice Voucher program (HCV). By increasing subsidy generosity in high-rent neighborhoods, SAFMR was intended to expand voucher households' access to high-opportunity areas. Using Dallas, the first metropolitan area to adopt SAFMR, I combine difference-in-differences evidence with a simple structural model of neighborhood choice of unsubsidized, non-voucher households to quantify how this redesign reshaped rent prices, residential sorting, and welfare for households not directly receiving housing assistance.

The empirical results show that SAFMR has led to changes in the spatial distribution of both voucher and non-voucher households and rent prices in the area. While the policy successfully relocated many voucher households from high-poverty neighborhoods to higher-opportunity areas, these movements triggered broader general equilibrium responses. Rents increased in high-opportunity neighborhoods and declined in low-opportunity neighborhoods, leading to a more polarized rent equilibrium. At the same time, it led to a more integrated equilibrium in terms of demographic composition across neighborhoods. Income and racial segregation declined as low-income and minority voucher households moved into traditionally high-rent neighborhoods and middle-income households re-sorted toward lower-opportunity areas.

Building on reduced-form evidence on residential equilibrium changes, I estimated a simple structural model to shed light on the welfare implications of these equilibrium changes. Instituting SAFMR and replacing metropolitan-wide payment standard with ZIP code-level ones generated modest welfare losses for high-income, non-voucher households through higher rents, while producing sizable welfare gains for low-income, non-voucher households through lower rents and reduced exposure to concentrated poverty in low-opportunity areas.

The welfare analysis also highlights that HCV itself, regardless of the design, imposed significant welfare costs on low-income households without voucher assistance. The voucher program itself inevitably concentrates poverty and housing demand in low-opportunity areas, a place where these unsubsidized low-income households are most likely to live. Relative to a metropolitan-wide payment standard, however, SAFMR mitigates this burden by redistributing it more evenly across the income distribution. The model further shows that housing supply elasticity plays a critical role in welfare impact with more inelastic markets exhibiting larger welfare loss for the lowest-income non-voucher households.

By increasing low-income voucher households' access to higher opportunities, HCV, along with its redesigned SAFMR, succeeded in providing more housing options for voucher households. However, the re-sorting of both voucher and non-voucher households altered the dynamics of the rental market and residential equilibrium. This policy inadvertently causes complex ripple effects that extend beyond its primary beneficiaries.

Although Small Area Fair Market Rents is a specific institutional setting, the lessons from the findings extend well beyond the design of voucher payment standards. At its core, the analysis speaks to a broader and increasingly central policy question: what happens when large numbers of low-income and minority households gain better access to neighborhoods that have historically been more expensive and low-poverty with greater "opportunities?" As policymakers place growing emphasis on mobility-oriented interventions and access to opportunity-rich neighborhoods, understanding the general equilibrium responses of housing markets becomes essential. This paper shows that such policies may inevitably reshape residential equilibrium and welfare for households far beyond the direct beneficiaries.

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A Appendix: Data

A.1 Standardizing and Harmonizing Picture of Subsidized Households Data

The Picture of Subsidized Households (PoSH) data is an annual data on voucher usage across various geographical definitions. The tract-level data prior to 2012 is based on the 2000 definition of Census tracts. However, post-2012 data are based on the 2010 definition. For geographic consistency across the years, I standardized and harmonized the geographic definition to follow the one from 2010 following the Longitudinal Tract Database (Logan et al., 2014).

The zip code-level data is then created by aggregating (or disaggregating) the tract-level data from 2007 to 2022. The process involved HUD's United States Postal Service (USPS) ZIP code-Census tract crosswalk files that map each Census tract to its respective zip codes. The crosswalks provide the residential ratio of each tract that is part of a specific zip code. I simply assigned the number of voucher households given in the tract-level data multiplied by this ratio to each zip code. Then, I aggregated the data to sum the counts of the voucher households for each zip code. I used the original tract-level data with the 2000 geographic definition to create zip code-level data for years from 2007 to 2011 and the other with the 2010 definition to create zip code-level data from 2012 to 2022. I used the crosswalk from the first quarter of 2010 to harmonize data from 2007 to 2010, whereas crosswalks from the fourth quarter of each respective year were used to harmonize data from 2011 to 2022.

B Appendix: Empirical Analysis

B.1 Supporting Arguments for Parallel Trend Assumption

One caveat of implementing the canonical 2×2 difference-in-differences in this research setting is that the data limitation prevents me from explicitly testing for the parallel assumption trend that is needed for proper identifications. In this section, I provide descriptive facts about the Dallas metropolitan area and its respective control metropolitan areas to lend supporting arguments for the parallel trend assumptions that I make throughout the paper.

The parallel trend assumption that I make in the rent price analysis is that the trends in the housing market would be the same in both the neighborhoods in the Dallas metropolitan area and the comparable neighborhoods in other control metropolitan areas in the absence of policy implementation. Examining the parallel trends down at the neighborhood level is not possible because of the data constraint. However, it is possible to assess the trends of the housing market at the metropolitan level over time.

Figure C.4 illustrates the trends in home values in the left panel and the number of home sales in the right panel from 2008 to 2020 with vertical lines placed in 2011.[42] The home values, as measured by Zillow's Home Value Index (ZHVI) in $1,000, show fairly parallel trends in the pre-treatment years. The number of home sales, as measured by the Sales Count Nowcast data from Zillow, also shows parallel trends in the pre-treatment years among Dallas and control metros with the exception of two control metros possibly violating it.

An analogous parallel trend assumption is required to properly identify the difference-in-differences coefficients for the income and racial compositions as well. More specifically, I need to assume that the general trends in the income and racial compositions in neighborhoods in Dallas would be the same as those in control metropolitan areas in the absence of the policy. To descriptively support this assumption, I use the metropolitan-level decennial Census data from 1990, 2000, 2010, and 2020 and plot the trend of racial compositions in Figure C.5 for white, Black, and Hispanic populations. The trends for all three race groups seem to follow parallel trajectories from 1990 to 2010 with a declining trend for the general white population, an increasing trend for the Hispanic population, and a stable trend for the Black population.

B.2 Housing Supply

The analyses of neighborhood rent prices and demographic compositions potentially require extra attention as Dallas is a housing elastic area and the number of housing units has been expanding

[42] I left out values for years prior to 2008 to abstract away from the trends caused by the financial crisis during 2007 and 2008 and the trends leading up to the crisis.

recently. I document this in Figure C.6 where I plot the total number of owner-occupied and renter-occupied housing units in the Dallas metro and other control metros from 1990 to 2020 on the left and right panels, respectively.

Clearly, there is a more rapid growth of housing units in the owner-occupied market when compared to other control metropolitan areas. However, the size of the renter-occupied housing units remains constant and comparable to other metros, suggesting that the recent expansion of housing supply in Dallas was mostly for owner-occupied units.

Given that the voucher households trigger changes in the housing market through the renter-occupied market, the descriptive fact above leads me to believe the housing supply had little to no impact on forming rent prices. Also, the increase in housing supply—if anything—is commonly associated with a decline in the overall market rate rent values (Asquith et al., 2023). Thus, if there was indeed a surge in the number of housing units in Dallas, my rent coefficients will capture lower bounds estimates, suggesting that in a housing inelastic area, the effects would have been even more pronounced.

In addition, I document trends in housing supply in the Dallas metro by neighborhood opportunity types from 2012 to 2020 in Figure C.7. The total number of housing units increased rapidly in high-opportunity neighborhoods, whereas the numbers in both mid- and low-neighborhoods remained stable as picture in the left panel. As shown in the right panel, most of the new constructions happened in high-opportunity neighborhoods. These descriptive facts give strong analytical support that the increases in rent prices in high-opportunity neighborhoods that I document in the main text are the lower-bound estimates, whereas the changes in mid- and low-opportunity neighborhoods are the true estimates.

The same argument of the increasing housing supply in Dallas could be used to challenge the estimates that I found for income and racial composition. However, given that I analyze the change in the compositions with the shares of relevant groups in different neighborhoods, the increasing housing supply does not add any complication to my analysis.

B.3 Supplementary Rent Analysis: Distributional Synthetic Control

To supplement the rent price analysis, I employ a new synthetic control approach called "distributional synthetic control", proposed by Gunsilius (2023), to assess the changes in the *overall distribution* of rents in the Dallas metropolitan area after the policy change. The standard synthetic control method relies on geographically aggregated-level characteristics (e.g. mean and median rent price of metropolitan areas) to create a "synthetic" version of a treated unit (Abadie et al., 2015; Alberto Abadie and Hainmueller, 2010).[43] However, the distributional synthetic control approach

[43]See Abadie (2021) for a recent literature review of the synthetic control methods.

makes use of disaggregated-level data to create a synthetic version of the treated unit and enables the researchers to assess the treatment effects at different percentile points in the distribution.

Within the setting of this study, the distributional synthetic control approach creates a synthetic version of the rent distribution in Dallas over time by matching the distributions of rent prices in the pre-treatment years. Using weights calculated for each metropolitan area in the donor pool, the counterfactual distributions of rent prices in the post-treatment periods are constructed. Then, the treatment effect of SAFMR at various points in the distribution can then be calculated by subtracting the counterfactual distribution from the actual distribution at the quantile of interest.

To put this idea formally, I first define the quantile function in the usual way as follows

$$F^{-1}(q) := \inf_{y \in \mathbb{R}} \{F(y) \geq q\} \quad \text{for} \quad q \in (0, 1)$$

where $F(y)$ is the corresponding cumulative distribution function of outcome y. Here, y will represent gross rent prices in each metropolitan area at different quantiles.[44] Consider I have housing unit-level data on $m = 1, \ldots, M + 1$ metropolitan areas with $m = 1$ being the treated metropolitan area, Dallas, over $t = 1, \ldots, T$. with $t = T_0$ being the treatment year (i.e. 2011). I denote Y_{mt} as the rent (home) values I observe in the data with $Y_{mt,N}$ is the outcome that would have been observed absent the treatment and $Y_{mt,I}$ is the outcome that would have been observed when exposed of treatment.

Analogous to the classical synthetic control setting, the goal would be to estimate the counterfactual quantile function of the treated unit had it not received the treatment. In particular, the counterfactual quantile function is formed as follows.

$$F^{-1}_{Y_{1t,N}}(q) = \sum_{m=2}^{M+1} \lambda^*_m F^{-1}_{Y_{mt}}(q)$$

The key is to calculate the optimal set of weights, λ^*_m, to be put on each metropolitan area in the donor pool to form synthetic Dallas in each pre-treatment period $t \leq T_0$. Gunsilius (2023) proposes to find the set of optimal weights from the unit simplex Δ^M by minimizing the 2-Wasserstein distance between the distribution of Dallas and those of other metropolitan areas in the donor pool. Formally put, the optimal weights for each pre-treatment period are found by solving the following

[44] Gross rent prices are controlled for the number of bedrooms, housing unit characteristics, and time trends for each metropolitan area. This way, the distributional synthetic control approach allows me to match the "shape" of the distributions rather than the absolute levels of rent prices.

minimization problem.

$$\overrightarrow{\lambda}_t^* = \underset{\overrightarrow{\lambda} \in \Delta^M}{\operatorname{argmin}} \int_0^1 \left| \sum_{m=2}^{M+1} \lambda_m F_{Y_{mt}}^{-1}(q) - F_{Y_{1t}}^{-1}(q) \right|^2 dq \tag{7}$$

Once the optimal weights are found for each pre-treatment period, the optimal weight to be put on each of the donor metropolitan areas is calculated by the weighted average of the weights over all pre-intervention periods. I choose equal weights following the paper's recommendation as follows.

$$\overrightarrow{\lambda}^* = \sum_{t \leq T_0} \frac{1}{T_0} \overrightarrow{\lambda}_t^*$$

I form the donor pool of metropolitan areas that the weights are going to be optimized on with the following criteria. I only keep the metropolitan areas with more than 2,500 voucher households present in 2010.[45] This is an important restriction as the metropolitan area has to have HCVP in place with a sizable number of voucher households. I chose 2,500 as the minimum, as the number corresponds with the criteria to select 23 additional metropolitan areas that were mandated to use SAFMR in 2018. I then keep the metropolitan areas where I have complete rent distribution data from 2006 to 2017. Also, individual rent data are controlled for the number of bedrooms.

I first examine the compatibility of the distributional fits between the actual and synthetic rent distributions of Dallas. As an illustrative example, I present a synthetic fit for one of the pre-treatment years–specifically, 2009–in the left panel of Figure C.8. The figure contrasts the actual and synthetic distributions of gross rents. The synthetic distribution, depicted by the dashed-orange line, closely mirrors the actual rent distribution in the Dallas metropolitan area, represented by the solid blue line. This alignment suggests that the optimal weights are appropriately chosen from Equation (7) and that the synthetic Dallas has been accurately constructed.

The right panel of Figure C.8 displays the counterfactual distribution of rents in synthetic Dallas (represented by the dashed-orange line) and the actual rent distribution in Dallas (depicted by the solid blue line) for one of the post-treatment years (2014) as an example. The counterfactual distribution embodies the cumulative distribution function of gross rents that would have been in place in Dallas had SAFMR policy *not* been implemented. Similar to the classical synthetic control setting, the horizontal distance between the two distributions can be interpreted as the treatment effect of SAFMR at each point in the distribution. A clear divergence between the two distributions suggests that the policy has had differing effects on rent prices at different points in the distribution three years after policy intervention. More specifically, rent prices increased at the upper end of the distribution, whereas they decreased at the lower end.

[45]Dallas had about 30,000 voucher households in 2010. I also restrict the donor pool to have more than 5,000 and 10,000 HCVP-contracted units in 2010 for robustness checks, and the results remain consistent.

To summarize the treatment effect, I average the treatment effects across all post-treatment years from 2012 to 2017 for each quantile and present the mean estimates in Figure C.9.[46] The figure reveals a clear price increase of approximately 2% at the upper end of the distribution from the 60th to the 90th quantiles. Conversely, the lower end of the distribution witnessed a price decline of a similar magnitude from the 20th to the 50th quantiles.

This result reinforces the neighborhood-level rent price analysis in the above section. The lower end of the rent distribution in high-opportunity neighborhoods experienced an increase in price, while the upper end of the rent distribution in low-opportunity neighborhoods experienced a decrease in price. While the distributional synthetic control results depict a smaller magnitude of the effects, they align with the empirical narrative of the potential effect of this policy as outlined in Section 3. The policy made the units in the upper distribution of the rents more expensive while making those in the lower end cheaper in similar magnitudes.

B.4 Income Composition Analysis with Distributional Synthetic Control

In this section, I extend the use of the distributional synthetic control method to evaluate how the *distributions* of household income evolved in different opportunity neighborhoods in response to the policy change. In contrast to the metropolitan-level application of distributional synthetic control as presented in Section B.3, I implement this approach at the neighborhood level, employing household-level data drawn from the InfoUSA dataset. Specifically, I match the household income distribution of each ZIP code in Dallas with corresponding ZIP codes in the metropolitan areas within the donor pool, categorized by their respective opportunity types.

Figure C.10 presents the results by neighborhood opportunity types. For each neighborhood, I average the treatment effects at all quantiles across the post-treatment years from 2012 to 2017. I then collect all such estimates and create whisker plots in the figure. As indicated by the leftward shift of the whisker plot in the lower end, the first-panel result suggests the lower end of the household income distributions in high-opportunity neighborhoods became poorer after the policy change. In other words, the households at the lower end of the household income distributions in high-opportunity neighborhoods have less household income than before the policy. The result is indicative of the fact that the policy induced an increase in the number of low-income voucher households in high-opportunity neighborhoods. In the mid-opportunity neighborhoods, the household incomes seemed to have mildly increased post-policy in the middle and upper parts of the distribution. The result suggests that high-income households who were originally living in high-opportunity neighborhoods may have trickled down to mid-opportunity neighborhoods. The

[46]Note that I only display treatment effects from the 10th to the 90th quantile points as the distributional synthetic control match tends to underperform in matching the extreme-low and upper ends of the distributions.

last figure suggests that low-opportunity neighborhoods did not seem to have experienced much change in the income composition.

B.5 Dealing with Missing Key Neighborhood Attributes in Model Estimation

In Section 6, I estimate the preference parameters for non-voucher households using data from the 2006-2010 and 2015-2019 ACS. Unfortunately, some of the key neighborhood attributes required for the estimation are unavailable for certain Census tracts, especially in the 2006-2010 ACS. A prime example of missing attributes is the median gross rent variable, which I use to proxy for neighborhoods' rent levels.

For an initial imputation approach, I capitalize on the gross rent distribution data from the ACS. Specifically, this data reveals the count of rental units within distinct gross rent intervals. By assuming a uniform gross rent distribution within each segment, I can approximate the probable median gross rent and utilize this value to substitute the missing data points in the original set.

The remaining missing values–the median gross rents included–are supplanted using the ZIP code characteristics data from the ZIP code-level ACS. More specifically, I replace the missing values with corresponding numbers from the ZIP code that has the highest residential ratio for the relevant tract in each respective year. For the 2006-2010 tract-level ACS, I utilized data from the 2007-2011 ZIP code-level ACS to fill in the gaps. All dollar-valued variables from the 2007-2011 ACS (originally denominated in 2011 dollars) were adjusted to 2010 dollars using the CPI. The 2015-2019 ZIP code-level ACS was used to replace missing values in the tract-level ACS of the same year.

A few key variables still remain missing for some of the tracts even after the procedures described above. To avoid this issue, I dropped 5 of these tracts in estimation. In addition, I dropped 2 additional tracts in estimation because they had less than 5 households present. In estimation, I dropped a total of 7 tracts out of the total 897 tracts in the Dallas metropolitan area.

B.6 Solving for Equilibrium

The algorithm used to solve for equilibrium follows closely that given in Almagro et al. (2023). Similar to their work, I wish to find a vector of endogenous neighborhood amenities, namely the rent prices and share of poor households (i.e. households in the first income-quartile group inclusive of voucher households), given the exogenous neighborhood characteristics and preference parameters. More specifically, given $\mathbf{X}$, ξ, and α, I want to find vectors of $\mathbf{P}$ and $\mathbf{L}$ that clear the market as follows:

$$\begin{cases} D_j(\mathbf{P}, \mathbf{L}, \mathbf{X}, \xi; \alpha) = S_j(P_j) \\ \frac{D_j^L(\mathbf{P},\mathbf{L},\mathbf{X},\xi;\alpha)}{D_j(\mathbf{P},\mathbf{L},\mathbf{X},\xi;\alpha)} = L_j \end{cases}$$

for all neighborhoods j.

To solve for the equilibrium, I define excess demand functions for both housing ($\mathcal{EDH}(\cdot)$) and share of poor households ($\mathcal{EDL}(\cdot)$) as

$$\mathcal{EDH}(\mathbf{P}, \mathbf{L}) = \begin{bmatrix} D_1(\mathbf{P}, \mathbf{L}) - S_1(P_1) \\ \vdots \\ D_J(\mathbf{P}, \mathbf{L}) - S_J(P_J) \end{bmatrix} \quad \text{and} \quad \mathcal{EDL}(\mathbf{P}, \mathbf{L}) = \begin{bmatrix} \frac{\bar{D}_1^v + D_1^1(\mathbf{P},\mathbf{L})}{D_1(\mathbf{P},\mathbf{L}))} - L_1 \\ \vdots \\ \frac{\bar{D}_J^v + D_J^1(\mathbf{P},\mathbf{L})}{D_J(\mathbf{P},\mathbf{L}))} - L_J \end{bmatrix}$$

where $\bar{\mathcal{D}}_j^v$ are the fixed number of voucher households in each neighborhood that will remain fixed throughout the procedures to solve for the equilibrium. As described in Section 7, I do not explicitly model voucher households' residential decisions and rely on manually and reasonably choosing their location decisions from outside of the model.

An equilibrium is found whenever the excess demand functions equal to 0 (i.e. $\mathcal{EDH}(\mathbf{P}, \mathbf{L}) = 0$ and $\mathcal{EDL}(\mathbf{P}, \mathbf{L}) = 0$). I perform an iterative procedure to find an equilibrium as follows. I first specify my initial guesses for rent price and share of poor households for each neighborhood as $\mathbf{P}^0$ and $\mathbf{L}^0$. For each guess, I compute the excess demand functions. If the equilibrium is not found at n-th iteration, I update the guesses as follows

$$\mathbf{P}^{n+1} = \mathbf{P}^n + \tau_P \cdot \mathcal{EDH}^n \quad \text{and} \quad \mathbf{L}^{n+1} = \mathbf{L}^n + \tau_L \cdot \mathcal{EDL}^n$$

where τ_P and τ_L are tuning parameters for updated guesses for the next iteration. I slowly update the guesses by taking fine parameters as $\tau_P = \tau_L = 0.02$. I update the guesses in the positive direction because the rent prices and the share of poor households act as congestion forces. I set the tolerance as follows

$$||\mathcal{EDH}(\mathbf{P}^n, \mathbf{L}^n)||_\infty < 0.05 \quad \text{and} \quad ||\mathcal{EDL}(\mathbf{P}^n, \mathbf{L}^n)||_\infty < e^{-4}$$

This is relatively a lenient tolerance to set. However, this allows for faster convergence in an accurate manner. I confirm that having stricter tolerance criteria leads to the same equilibrium.

B.7 Discussions on Model Fit

In this section, I discuss how well my estimated model performs and fits the equilibrium rent prices and share of poor households. To do so, I simply simulate equilibrium vectors of **P** and **L** in 2019 given the exogenous neighborhood characteristics **X** from the actual ACS data, the estimated fixed effects, $\hat{\lambda}_j$'s and $\hat{\lambda}_t$'s, and the estimated scalars of unobserved neighborhood amenities, ξ. The equilibrium vectors found during the process should coincide well with the actual data.

I plot the joint distributions of rent prices and shares of poor households of neighborhoods in the actual data and the simulated version in Figure C.13. The distribution of the two endogenous neighborhood attributes in the actual data is shown in yellow dots, whereas that of the simulated equilibrium with the estimated model is given in blue dots. I picture local polynomial regression fits in lines for each respective equilibrium. The model seems to do a good job of replicating the actual data but with some deviations in certain neighborhoods–especially at the extreme end of the distribution with low rents and high shares of poor households.

The poor fit at the lower-income neighborhoods in the distribution is likely due to the smoothing that I do for the estimation of preference parameters described in Section 6. More specifically, I take the distant-weighted average of the frequency estimates across neighborhoods to fix for the inconsistency in the assumed error structure in the model of having 0 or 1 share of a particular income group in a neighborhood. This smoothing procedure adds (or subtracts) a positive mass of households to neighborhoods that have 0 households from a particular income group given in the ACS data. This allows proper estimation of preference parameters, but the predicted shares of each income group from the model will be slightly off from the actual data.

To see this, I compute the predicted shares of each income group using

$$\hat{\sigma}^n_{jt} = \frac{\exp\{\hat{\delta}^n_{jt}\}}{\sum_{j'} \exp\{\hat{\delta}^n_{j't}\}}$$

where

$$\hat{\delta}^n_{jt} = \hat{\alpha}^n_P \ln P_{jt} + \hat{\alpha}^n_L L_{jt} + \hat{\alpha}^n_X X_{jt} + \hat{\lambda}^n_j + \hat{\lambda}^n_t + \hat{\hat{\xi}}^n_{jt}$$

and plot them against the observed shares in the data in Figure C.14. If the preferences were estimated with data that does not require smoothing, then I would expect all dots to be on the 45-degree diagonal lines in dashed gray suggesting a perfect fit. However, because of the smoothing, there are neighborhoods that are off-diagonal, especially for those in the Q1 and Q4 income groups. This is expected since the Q1 and Q4 households are those that are the most stratified in terms of residential equilibrium. These off-diagonal neighborhoods lead to preference estimates that give rise to a relatively poorer fit in the lower end of the neighborhood distribution.

B.8 Decomposition of Welfare into Rent Equivalence and Rental Income

In Figure C.15, I decompose the welfare impacts of SAFMR into two components: (i) rent equivalence corresponding to the first term in Equation (6) and (ii) flow of rental income corresponding to the second term in the same equation. I focus on discussing the decomposition result of the welfare of the first income quartile group as they are the most affected group. The positive welfare benefits accrued by this group are mainly driven by rent equivalence accounting for about 0.9% of their income. The rental income component, on the other hand, marginally mutes the positive gain from the rent equivalence. The interpretation is that the unsubsidized households in the first income quartile group who are renters experienced positive welfare change due to lower living costs in low-opportunity neighborhoods, whereas homeowners in the same income group experienced negative welfare change due to the depreciation of their housing portfolio.

C Appendix: Figures and Tables

Table C.1: List of HUD Metropolitan Areas Selected to Adopt SAFMR

HUD Metropolitan Area	Voucher Counts	Voucher Concentration	Percent Quality Units under SAFMR ≥ 110% MFMR
Metros with SAFMR in Place in 2011			
Dallas-Plano-Irving, TX Metro Division	28,135	1.54	0.25
Metros with SAFMR in Place in 2018			
Atlanta-Sandy Springs-Marietta, GA HUD Metro FMR Area	28,697	1.61	0.23
Bergen-Passaic, NJ HUD Metro FMR Area	11,503	1.58	0.27
Charlotte-Gastonia-Rock Hill, NC-SC HUD Metro FMR Area	7,951	1.84	0.25
Chicago-Joliet-Naperville, IL HUD Metro FMR Area	62,472	1.78	0.25
Colorado Springs, CO HUD Metro FMR Area	2,957	1.56	0.26
Fort Lauderdale-Pompano Beach-Deerfield Beach, FL Metro Division	10,486	2.16	0.27
Fort Worth-Arlington, TX HUD Metro FMR Area	12,620	1.60	0.28
Gary, IN HUD Metro FMR Area	3,305	1.74	0.21
Hartford-West Hartford-East Hartford, CT HUD Metro FMR Area	12,831	1.60	0.21
Jackson, MS HUD Metro FMR Area	4,742	1.85	0.30
Jacksonville, FL HUD Metro FMR Area	5,872	1.98	0.24
Monmouth-Ocean, NJ HUD Metro FMR Area	7,811	2.32	0.35
North Port-Bradenton-Sarasota, FL MSA	2,592	2.59	0.27
Palm Bay-Melbourne-Titusville, FL MSA	2,565	2.14	0.31
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD MSA	32,631	1.75	0.26
Pittsburgh, PA HUD Metro FMR Area	15,739	2.05	0.22
Sacramento–Arden-Arcade–Roseville, CA HUD Metro FMR Area	12,672	1.57	0.28
San Antonio-New Braunfels, TX HUD Metro FMR Area	14,633	1.96	0.26
San Diego-Carlsbad-San Marcos, CA MSA	27,970	1.71	0.30
Tampa-St. Petersburg-Clearwater, FL MSA	16,456	1.89	0.21
Urban Honolulu, HI MSA	4,146	1.62	0.39
Washington-Arlington-Alexandria, DC-VA-MD HUD Metro FMR Area	32,109	1.66	0.31
West Palm Beach-Boca Raton-Delray Beach, FL Metro Division	6,058	2.00	0.45
Metros Selected but Never Mandated			
Nassau County-Suffolk County, NY Metro Division	11,593	1.90	0.48
New York, NY HUD Metro FMR Area	119,362	1.70	0.21
Oakland-Hayward-Berkeley, CA Metro Division	28,355	1.55	0.28
Oxnard-Thousand Oaks-Ventura, CA MSA	5,612	1.58	0.37
San Jose-Sunnyvale-Santa Clara, CA HUD Metro FMR Area	14,307	2.14	0.21
Tacoma-Lakewood, WA Metro Division	5,341	1.55	0.34
Virginia Beach-Norfolk-Newport News, VA-NC HUD Metro FMR Area	12,291	1.70	0.28

Notes: The table above lists the HUD metropolitan areas that (1) adopted SAFMR policy in 2011, (2) adopted the policy in 2018, and (3) were initially chosen to adopt the policy in 2018 but did not come to effect. Voucher counts refer to the total number of vouchers being administered in the region; voucher concentration refers to the ratio of the percentage of voucher holders living in low-income areas to the percentage of all renters in the entire region; and percent quality units under SAFMR ≥ 110% MFMR refers to percent standard-quality rental stock located in ZIP codes where SAFMR is more than 100% of the metropolitan-wide FMR. The number of active vouchers as of June 2015 for each metropolitan area is listed on the right. *Source:* SAFMR Proposed Rule Area Selection Tool from HUD for which the values were calculated based on 2015 values.

Table C.2: Summary of Opportunity Measures by Neighborhood Opportunity in Dallas

Opportunity Measures	High Opportunity	Mid Opportunity	Low Opportunity
Small Area Fair Market Rents (2BR)	$1,116	$915	$744
Median Gross Rent	$1,219	$1,000	$812
Mean Income Rank Born to Parent in 10th Percentile	0.44	0.37	0.32
Mean Income Rank Rank Born to Parent in 25th Percentile	0.48	0.42	0.37

Notes: The table above shows averages of possible opportunity measures of neighborhoods by opportunity types in the Dallas metropolitan area. The first row shows the 2-bedroom Small Area Fair Market Rents set in 2011 for each Census tract. The data for median gross rent come from the tract-level 2007-2011 ACS and the last two rows come from the Opportunity Insights. The last two rows represent the mean predicted household income percentile rank of children living in each neighborhood born to parents in respective percentile ranks in the national household income distribution. Further details on the Opportunity Insights data can be found in **?**.

Table C.3: Neighborhood Characteristics Related to Voucher Household Movements by Opportunity Status

	Δ Number Voucher Households					
	> 0			< 0		
	High-Opp	Mid-Opp	Low-Opp	High-Opp	Mid-Opp	Low-Opp
Fair Market Rent ($)	-0.03	0.07	-0.03	0.02	-0.00	-0.12***
	(0.03)	(0.12)	(0.19)	(0.02)	(0.04)	(0.04)
% Minority	0.45***	0.31	0.11	-0.23***	-0.31***	-0.19*
	(0.17)	(0.23)	(0.33)	(0.07)	(0.07)	(0.10)
% Commute with Public Transportation	3.71***	1.51	2.02	0.10	-1.50**	-1.05**
	(1.35)	(1.62)	(1.92)	(0.52)	(0.60)	(0.48)
R-squared	0.13	0.04	0.05	0.12	0.14	0.12
Mean Change	25	36	47	-12	-21	-30
Observations	172	91	56	110	190	144

Notes: This table documents the relationship between the change in the number of voucher households and neighborhood characteristics. I estimate the relationship separately for Census tracts that had positive and negative change in the number of voucher households by neighborhood opportunity status. Change in the number of voucher households in each Census tract from 2012 to 2019 is regressed on zip code-level fair market rent levels in 2011, share of minority (including Black and Hispanic households) in the 2008-2012 ACS, and share of workers who commute with public transportation in the 2008-2012 ACS.

Table C.4: Estimates of Neighborhood Preference Parameters for Non-Voucher Households (OLS)

	Income Group			
	Q1	Q2	Q3	Q4
Log(Median Gross Rent)	-0.056	-0.098	0.087	0.051
	(0.073)	(0.062)	(0.062)	(0.081)
Share Poor	2.804***	-1.489***	-1.781***	-1.212***
	(0.187)	(0.159)	(0.160)	(0.209)
Tract Fixed Effects	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y
Additional Controls	Y	Y	Y	Y
Number of Tracts	890	890	890	890
Observations	1780	1780	1780	1780

Notes: This table presents OLS regression results of preference parameters for endogenous neighborhood attributes including median gross rent and share of poor households as defined by those in the first quartile income group (Q1). Exogenous neighborhood characteristics include share of owner-occupied housing units, share of workers commuting with public transportation, median number of rooms, median year of buildings built, share of buildings with 1 unit, and share of buildings with more than 50 units.

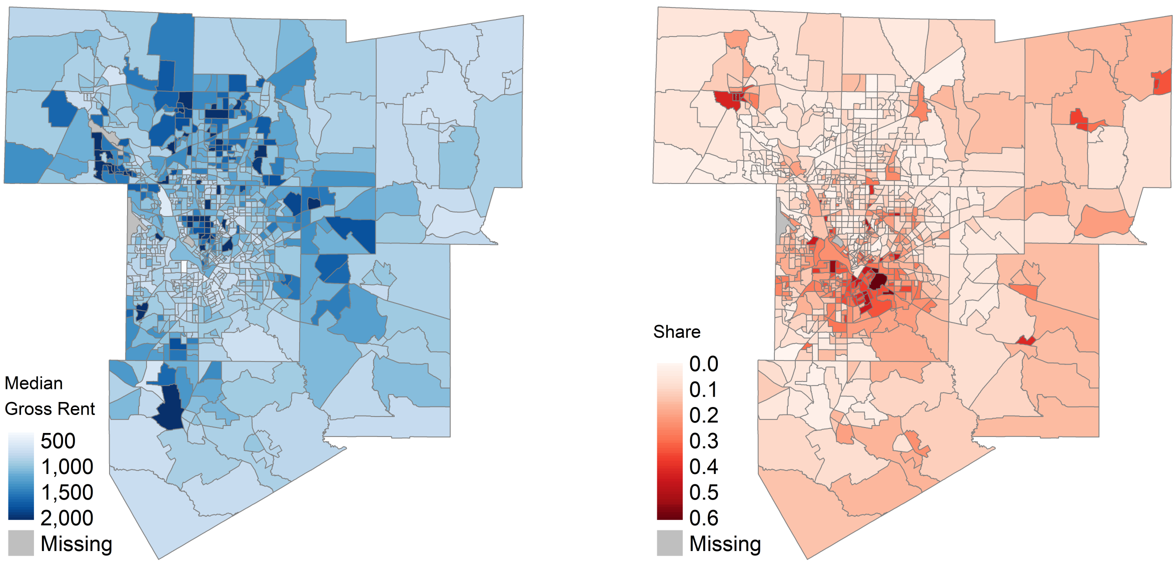
Table C.5: Summary Statistics of Demographic Groups in Dallas

	Demographic Group															
	Q1				Q2				Q3				Q4			
	All	White	Black	Hispanic	All	White	Black	Hispanic	All	White	Black	Hispanic	All	White	Black	Hispanic
Income ($)	22,200	22,424	20,346	24,043	56,703	57,350	55,793	56,043	97,283	98,122	96,231	95,380	225,286	233,622	193,226	195,949
Home Ownership	0.38	0.49	0.22	0.37	0.51	0.59	0.33	0.51	0.67	0.72	0.53	0.67	0.85	0.88	0.73	0.80
Share College+	0.18	0.25	0.14	0.07	0.31	0.38	0.32	0.11	0.44	0.49	0.43	0.21	0.66	0.68	0.60	0.42
Share of Households	1.00	0.40	0.25	0.28	1.00	0.48	0.19	0.27	1.00	0.57	0.14	0.20	1.00	0.71	0.08	0.10

Notes: The table above shows the summary statistics of different demographic groups broken down into (i) income groups or (ii) income × race groups. The statistics are based on the 2015-2019 ACS.

Figure C.1: Map of Dallas by Rent and Poverty Rate

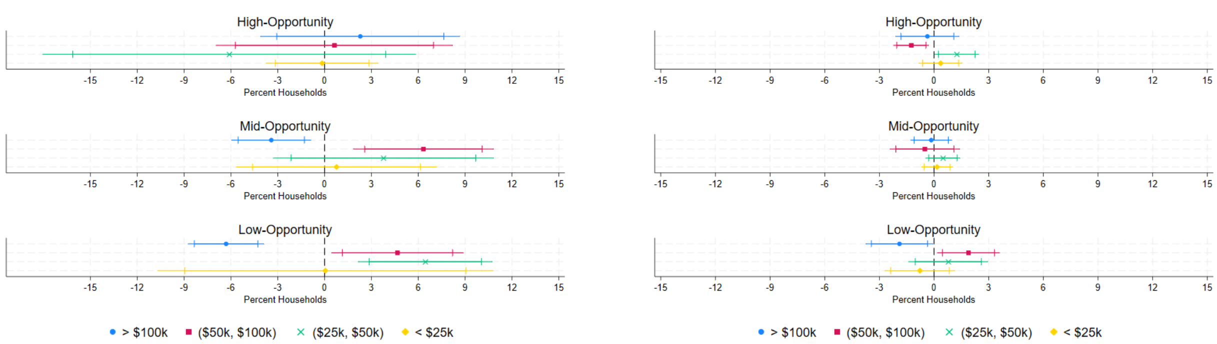
(a) Median Gross Rent (b) Below Poverty



Notes: The figures above show maps of Census tracts in Dallas based on the 2010 geographical designation. The left panel is a map of Census tracts in the Dallas-Plano-Irving, TX Metro Division with their respective median contract rents plotted. The right panel is based on the share of households living under the poverty line for each tract. Darker shades of color indicate higher rent and higher poverty, respectively. Both measures come from the 2008-2012 ACS.

Figure C.3: Income Compositions by Tenure Status

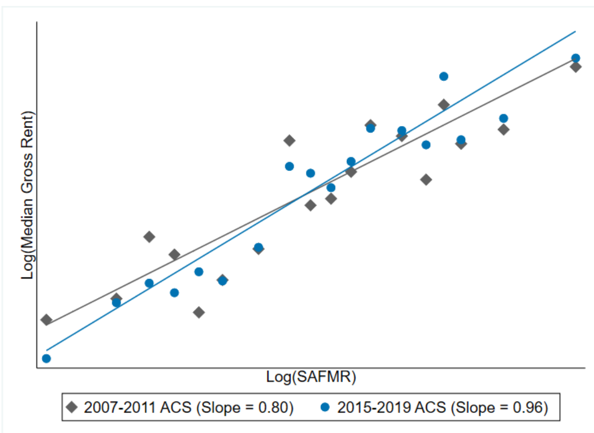
(a) Renters (b) Owners



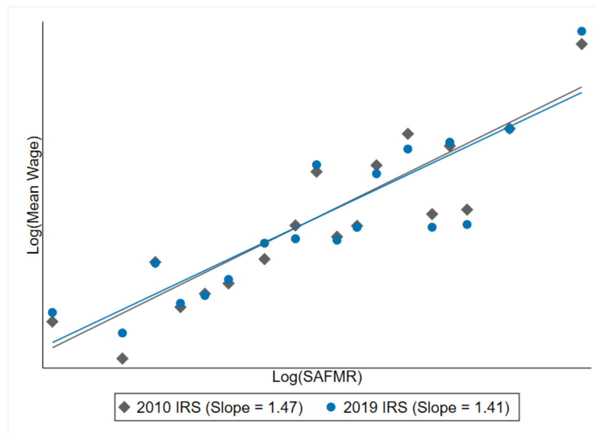
Notes: The figures plot the difference-in-differences coefficients for the share of households in different income bins by neighborhood opportunity types by tenure status. The left panel shows the shares among renters. The right panel shows the shares among owners. The standard errors are robust and clustered at the ZIP code level. Both 90 and 95 percent confidence intervals are shown in the figures.

Figure C.2: Long-Run Equilibrium - Empirical Version

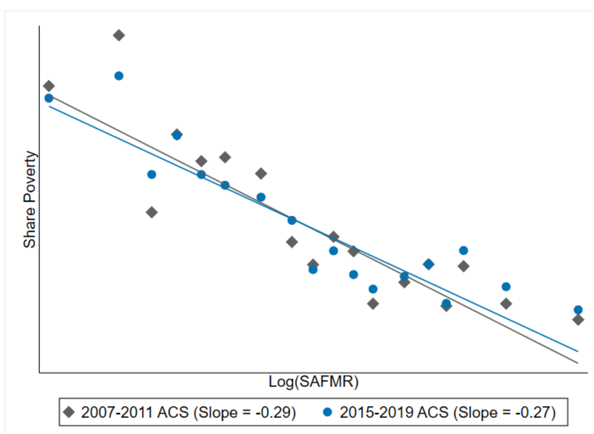
(a) Rent Price Gradients



(b) Wage Gradients



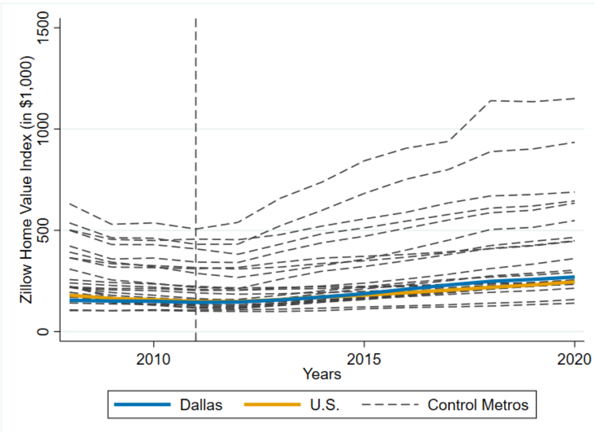
(c) Share Poverty Gradients



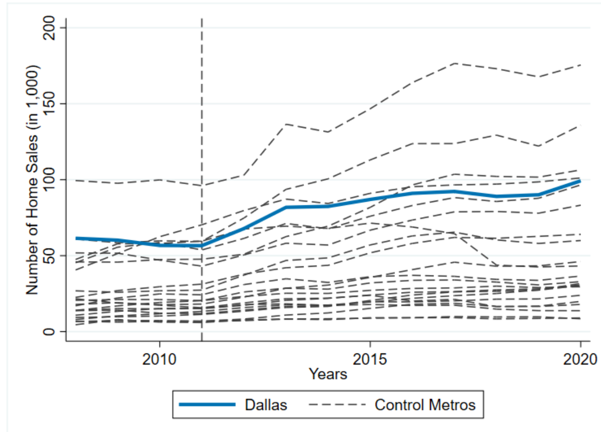
Notes: The figures above show the empirical version of the long-run gradients of each respective outcome variable. The gray lines represent the initial equilibrium before the policy change, whereas the blue lines represent the policy-induced equilibrium. All variables are demeaned for each year to make the gradients comparable across years.

Figure C.4: Trends in Housing Market in Select Metropolitan Areas and U.S. (2008-2020)

(a) Housing Price



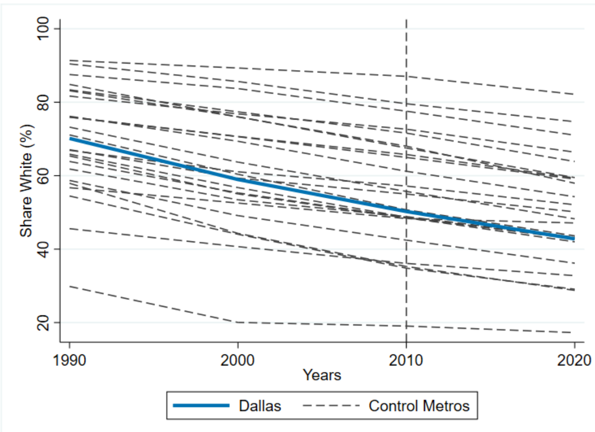
(b) Number of Home Sales



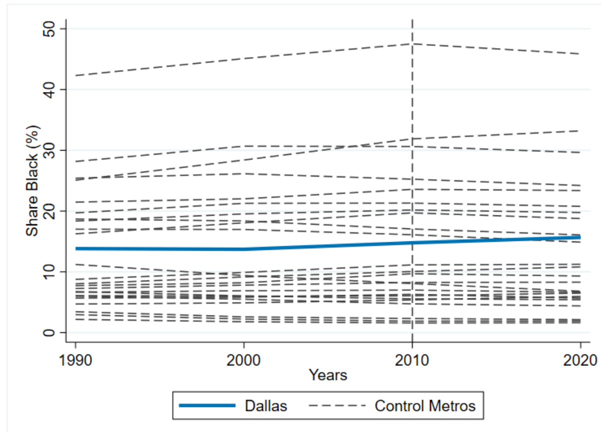
Notes: The figures above plot the trends in the housing market for both the Dallas metro and other select control metropolitan areas. The left panel plots the trend in housing prices as measured by Zillow's Home Value Index, and the right panel plots the trend in the number of home sales from Zillow's Sales Count Nowcast. Note that the number of sales in 2008 excludes January sales. The list of control metros includes Atlanta, GA; New York, NY; Charlotte, NC; Chicago, IL; Colorado Springs, CO; Miami, FL; Hartford, CT; Jackson, MS; Jacksonville, FL; North Port, FL; Palm Bay, FL; Philadelphia, PA; Pittsburg, PA; Sacramento, CA; San Antonio, TX; San Diego, CA; Tampa, FL; Urban Honolulu, HI; Washington, DC; San Francisco, CA; San Jose, CA; Virginia Beach, VA; Oxnard, CA; and Seattle, WA. *Source*: Housing Data - Zillow Research

Figure C.5: Trends in Racial Compositions in Select Metropolitan Areas and U.S. (1990-2020)

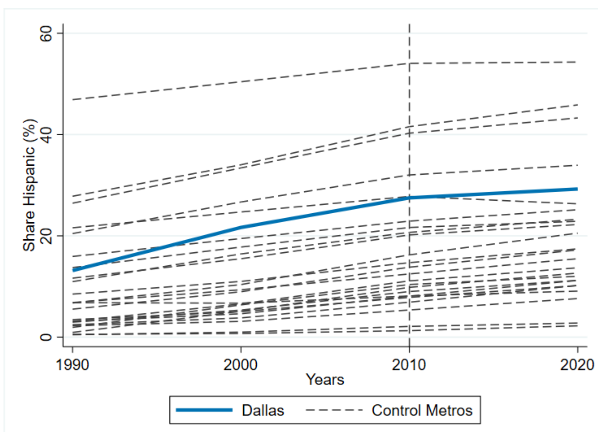
(a) Share White



(b) Share Black



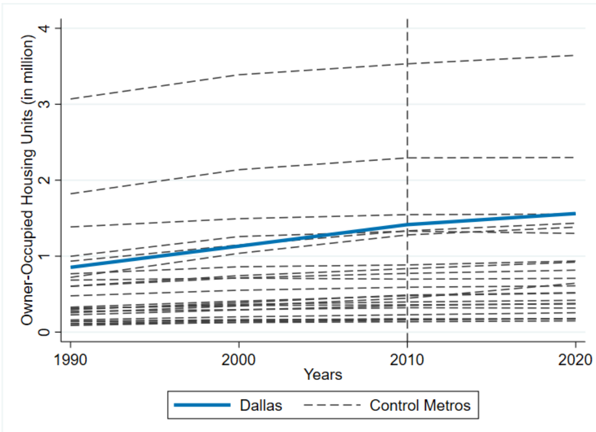
(c) Share Hispanic



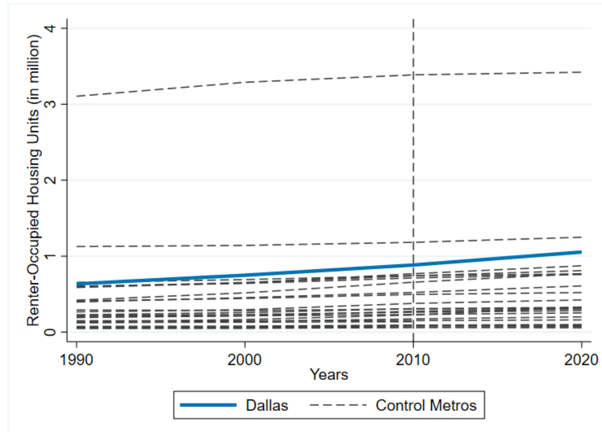
Notes: The figures above plot the racial makeups for both the Dallas metro and other select control metropolitan areas in the left and right panels, respectively. The list of control metros includes Atlanta, GA; New York, NY; Charlotte, NC; Chicago, IL; Colorado Springs, CO; Miami, FL; Hartford, CT; Jackson, MS; Jacksonville, FL; North Port, FL; Palm Bay, FL; Philadelphia, PA; Pittsburg, PA; Sacramento, CA; San Antonio, TX; San Diego, CA; Tampa, FL; Urban Honolulu, HI; Washington, DC; San Francisco, CA; San Jose, CA; Virginia Beach, VA; Oxnard, CA; and Seattle, WA.

Figure C.6: Trends in Occupied Housing Units in Select Metropolitan Areas and U.S. (1990-2020)

(a) Owner-Occupied Units



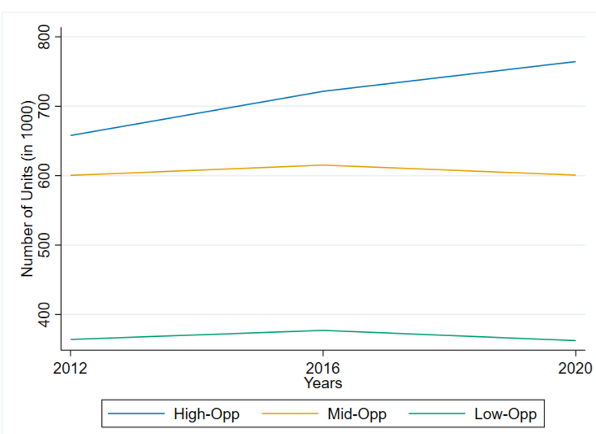
(b) Renter-Occupied Units



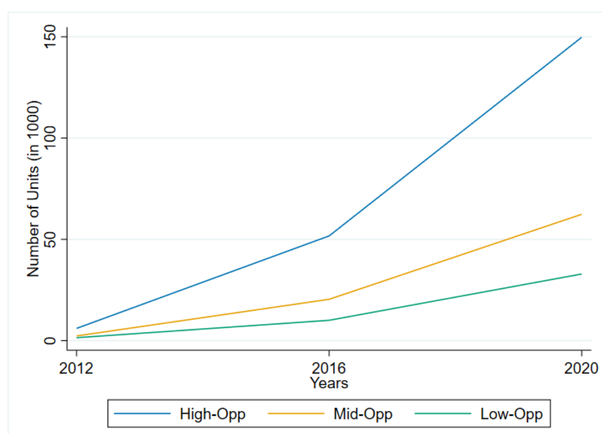
Notes: The figures above plot the trends in the number of owner- and renter-occupied housing units for both the Dallas metro and other select control metropolitan areas in the left and right panels, respectively. The list of control metros includes Atlanta, GA; New York, NY; Charlotte, NC; Chicago, IL; Colorado Springs, CO; Miami, FL; Hartford, CT; Jackson, MS; Jacksonville, FL; North Port, FL; Palm Bay, FL; Philadelphia, PA; Pittsburg, PA; Sacramento, CA; San Antonio, TX; San Diego, CA; Tampa, FL; Urban Honolulu, HI; Washington, DC; San Francisco, CA; San Jose, CA; Virginia Beach, VA; Oxnard, CA; and Seattle, WA.

Figure C.7: Trends in Housing Supply in Dallas

(a) Total Housing Units

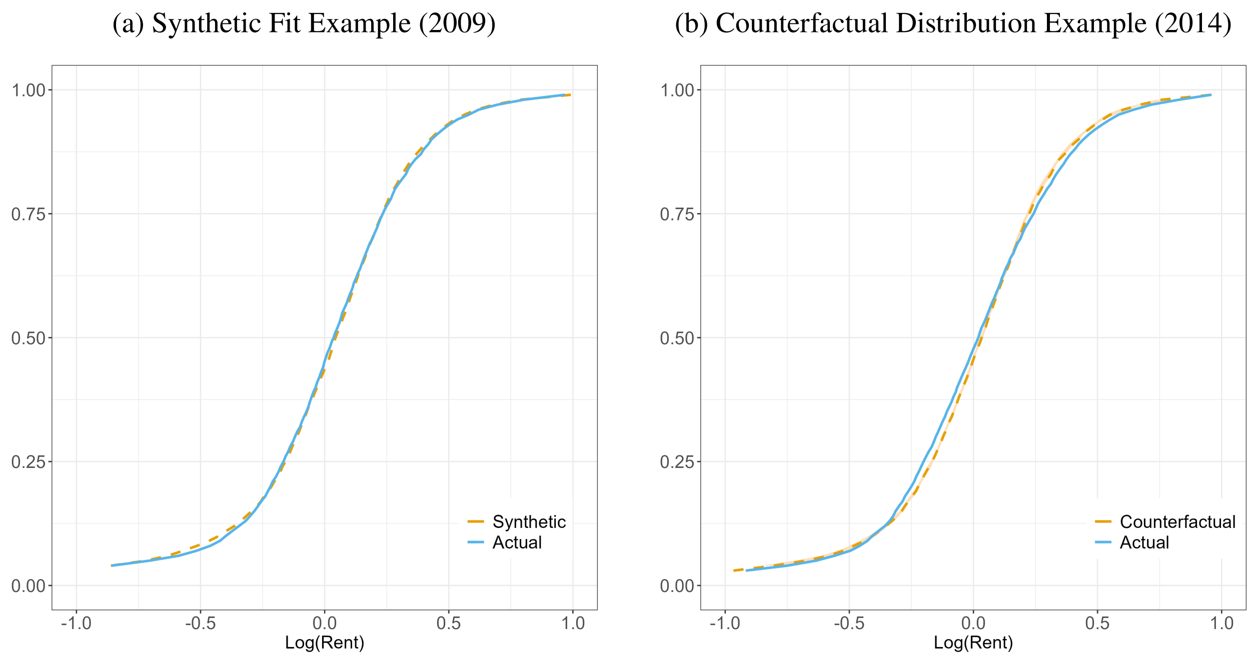


(b) Number of New Constructions (Built Post-2010)



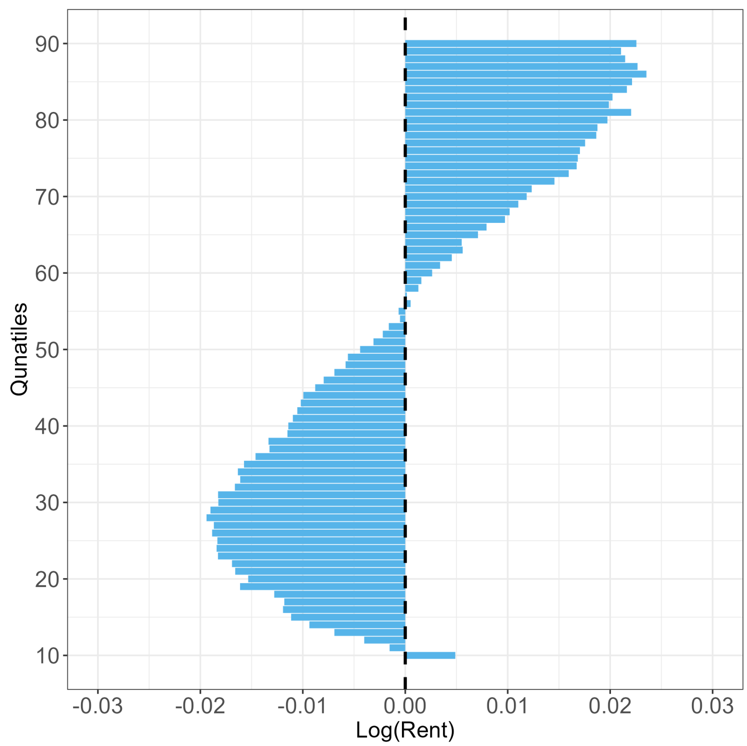
Notes: The figures above plot the number of total housing units (left panel) and new constructions as defined by those that are built after 2010 (right panel) in the Dallas metro by neighborhood opportunity types over the specified time period. The years 2012, 2016, and 2020 represent the 2008-2012, 2012-2016, and 2016-2020 ACS.

Figure C.8: Assessing Fit of Distributional Synthetic Control



Notes: The figure in the left panel shows the fit of the gross rent distributions of actual and synthetic Dallas in 2009 as one example from the pre-treatment years. The distribution for synthetic Dallas is based on the optimal weights constructed from the distributional synthetic control method for each year, $\overrightarrow{\lambda}_t^*$. The figure in the right panel shows the gross rent distribution of actual and synthetic Dallas in 2014 as one example from the post-treatment years. The counterfactual distribution is constructed using the weighted average of the optimal weights found for each pre-treatment year from the distributional synthetic control method, $\overrightarrow{\lambda}^*$.

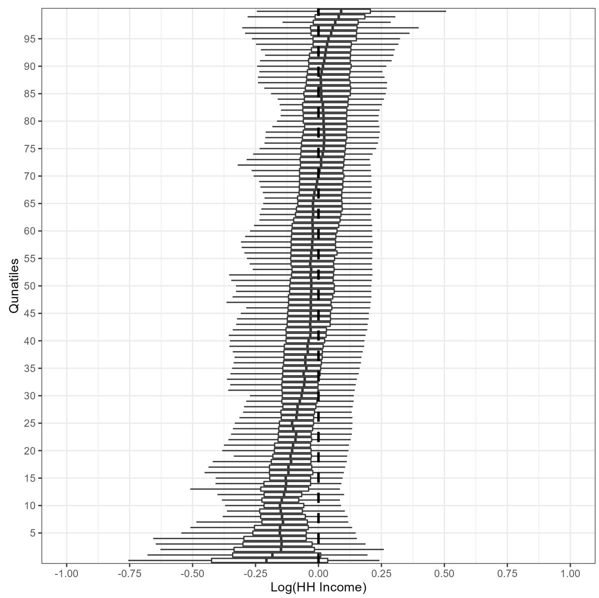
Figure C.9: Distributional Synthetic Control Treatment Effects Summarized



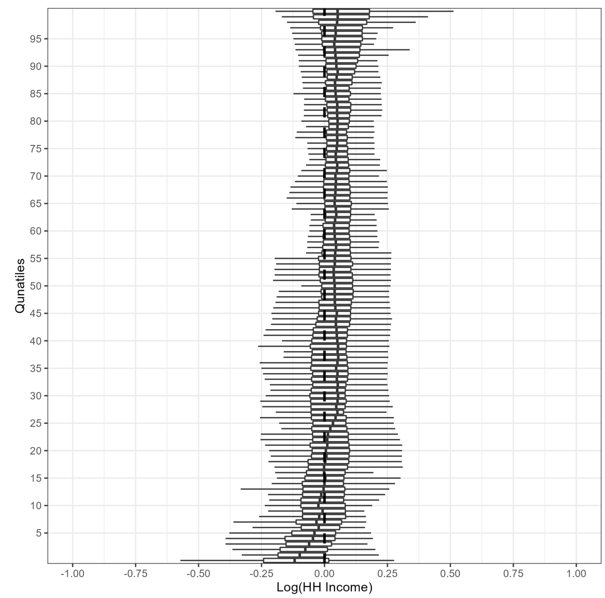
Notes: The figure above summarizes the treatment effects of SAFMR on gross rent distribution at quantiles from 2012 to 2017. The treatment effects are averaged across all post-treatment years from 2012 to 2017 at from 10th to 90th quantiles of the rent distributions.

Figure C.10: Household Income–Distributional Synthetic Control

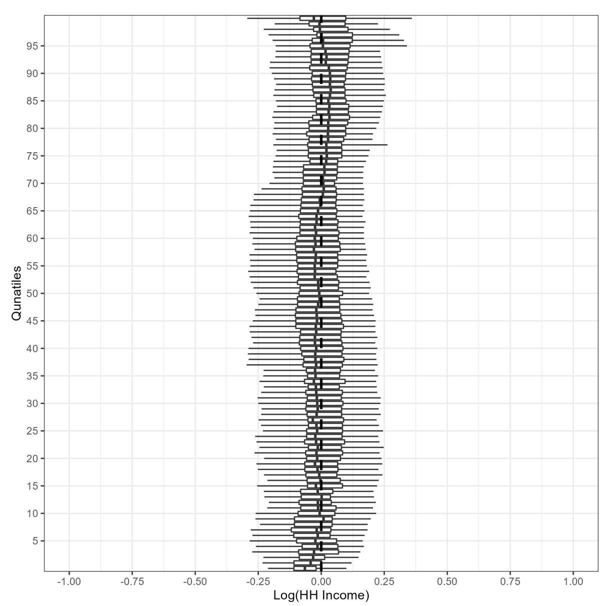
(a) High-Opportunity Neighborhoods



(b) Mid-Opportunity Neighborhoods



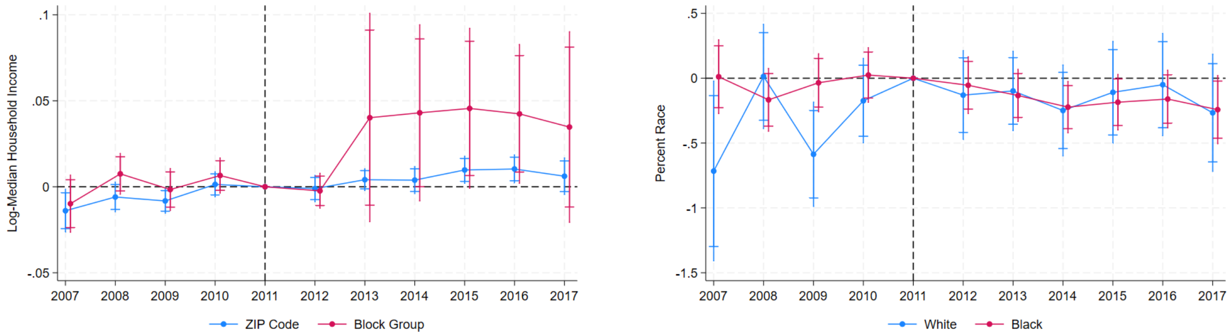
(c) Low-Opportunity Neighborhoods



Notes: The figures above depict whisker plots of the neighborhood-level treatment effects from the distributional synthetic control averaged across post-treatment years from 2012 to 2017 for each quantile. The distributional synthetic control has been performed for each ZIP code based on its opportunity type.

Figure C.11: Characteristics of In-Migrants to High-Opportunity Neighborhoods

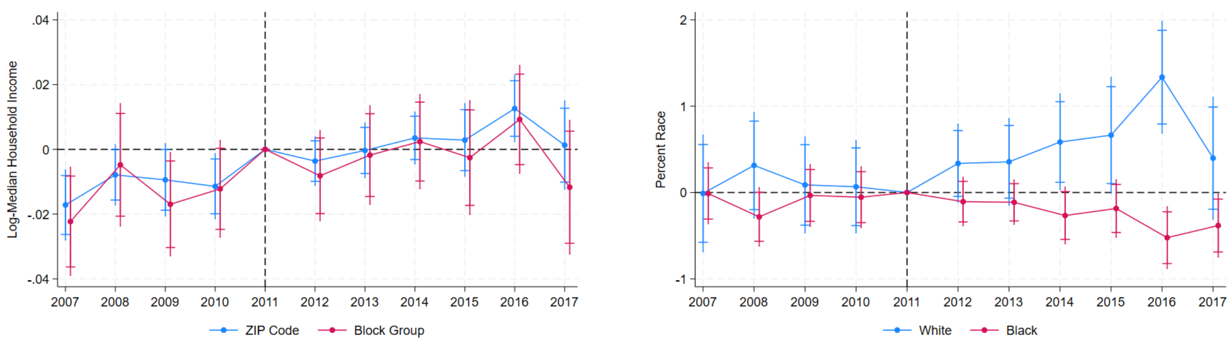
(a) Origin Neighborhood's Median HH Income (b) Origin Neighborhood's Racial Composition



Notes: The figures above plot the event-study coefficients of the effect of SAFMR on in-migration patterns to high-opportunity neighborhoods. In the left panel, the dependent variable is the log median household income of a neighborhood (either zip code or block group) an in-migrant originated from. The dependent variable in the right panel is the share of the respective race group of a zip code an in-migrant originated from. 95% confidence intervals are shown in the figures. The standard errors are clustered at the zip code level.

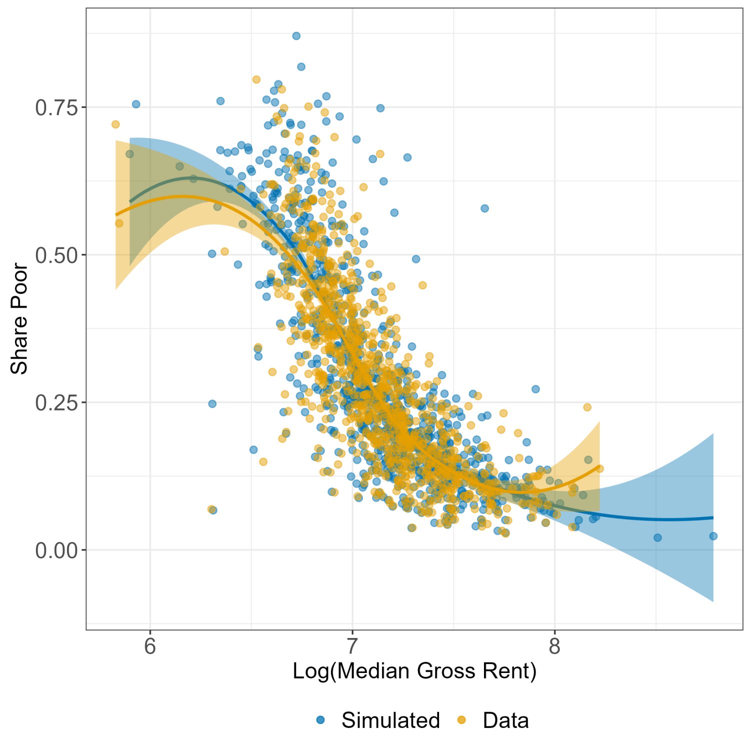
Figure C.12: Characteristics of In-Migrants to Mid-Opportunity Neighborhoods

(a) Origin Neighborhood's Median HH Income (b) Origin Neighborhood's Racial Composition



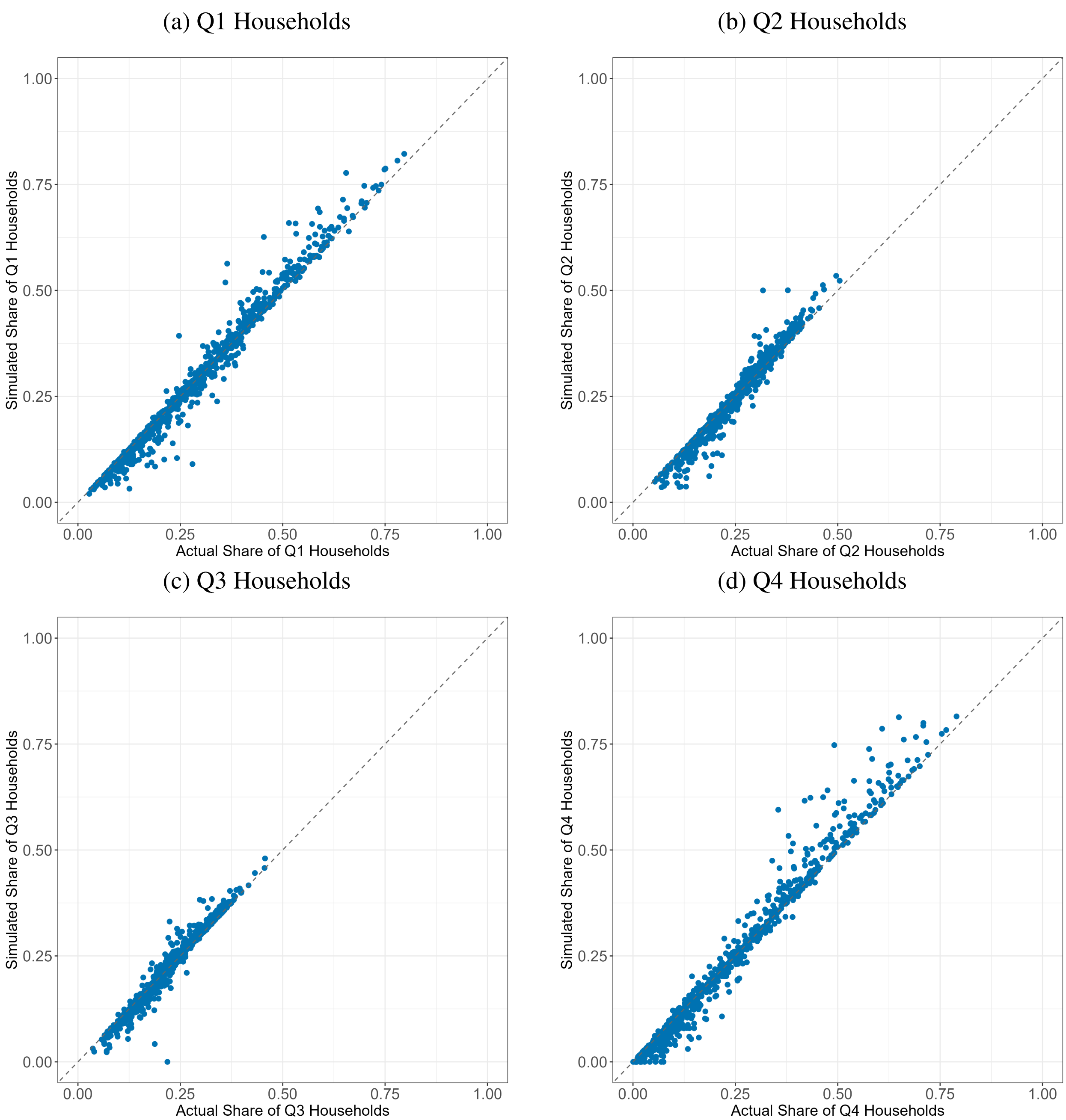
Notes: The figures above plot the event-study coefficients of the effect of SAFMR on in-migration patterns to mid-opportunity neighborhoods. In the left panel, the dependent variable is the log median household income of a neighborhood (either zip code or block group) an in-migrant originated from. The dependent variable in the right panel is the share of the respective race group of a zip code an in-migrant originated from. 95% confidence intervals are shown in the figures. The standard errors are clustered at the zip code level.

Figure C.13: Model Fit - Actual v. Simulated Equilibria



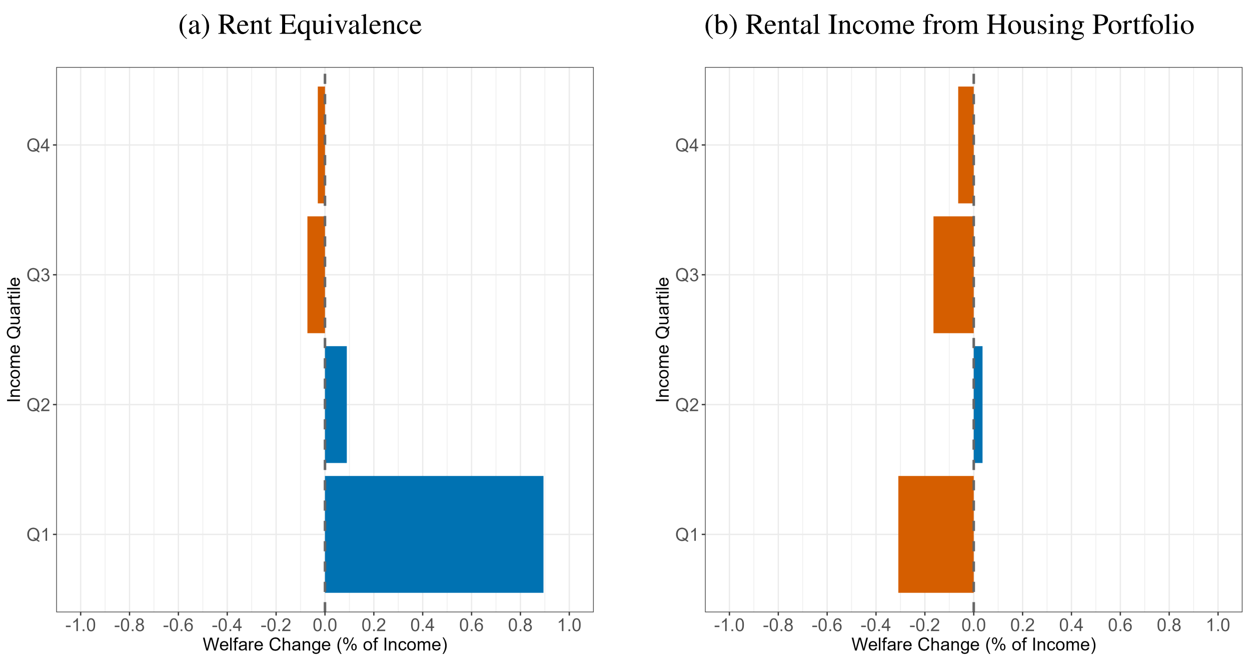
Notes: The figure plots the joint distribution of rent prices and shares of poor households in neighborhoods in Dallas. Yellow dots represent the distribution given in the 2015-2019 ACS data, whereas blue dots represent those that are simulated using the estimated model. Local polynomial regression fits are drawn for the two joint distributions.

Figure C.14: Model Predicted v. Actual Shares of Households in Income Groups



Notes: The figures above plot the predicted share of households in each respective income group using the estimated preference parameters against the share of households given in the 2015-2019 ACS.

Figure C.15: Decomposition of Welfare Impacts of SAFMR into Rent Equivalence and Rental Income



Notes: The figures above decompose the total welfare effect of implementing SAFMR into two components. The rent equivalent measures for each income group are shown in the left panel, whereas the rental income components are shown on the right.