Improving Access to Opportunity: Housing Vouchers and Residential Equilibrium*

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Abstract

This paper examines the effects of improving low-income households' access to high-rent, high-opportunity neighborhoods on the residential equilibrium. Amidst pervasive residential segregation, I study the Small Area Fair Market Rents, a re-design of the rental voucher program that increased subsidies in high-rent neighborhoods and allowed voucher families to relocate there. I find that it led to a more polarized rental market: rents rose in high-rent areas but declined in low-rent areas. In contrast, it fostered a more egalitarian equilibrium in terms of income and racial composition. While high-income non-voucher households experienced a modicum of welfare loss due to increased living costs, low-income counterparts benefited from reduced rents in low-rent neighborhoods. However, I find that the institution of the voucher program itself led to a substantial welfare loss for low-income households, the very population this program aims to assist. This research illustrates the broader implications of housing vouchers, underscoring the need to balance affordable housing, societal integration, and overall welfare.

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

Neighborhoods play a significant role in determining economic, educational, and health outcomes for both adults and children (Chyn and Katz, 2021).[1] Unfortunately, low-income minority households are disproportionately segregated into low-opportunity neighborhoods characterized by low levels of economic resources (Aliprantis et al., 2022; Bayer et al., 2021; Reardon et al., 2015).[2,3] This pattern of segregation is even more pronounced among subsidized households, including the families under the Housing Choice Voucher Program (HCVP), the largest federal housing subsidy program in the U.S. run by the Department of Housing and Urban Development (HUD) (Collinson et al., 2015; Galvez, 2010; Horn et al., 2014; Mazzara and Knudsen, 2019; Metzger, 2014). Given the importance of neighborhood effects, the growing debate has focused on how to better design the voucher programs to effectively improve low-income families' access to higher-opportunity neighborhoods (Bergman et al., 2019; Collinson and Ganong, 2018; DeLuca and Rosenblatt, 2017).

What would be the broader economic impact if a significant number of low-income households moved to better neighborhoods with higher housing prices and opportunities? I investigate the equilibrium impacts of enhancing low-income households' access to high-opportunity neighborhoods through increased voucher subsidies on the broader rental market and residential segregation. I further examine the welfare consequences of this voucher-induced equilibrium for *unsubsidized* households. The research centers around the Small Area Fair Market Rents (SAFMR), a re-design of the HCVP that effectively enabled low-income voucher families to relocate from low- to high-opportunity neighborhoods. It shifts a substantial part of the voucher households' demand for housing to high-opportunity neighborhoods, increasing the market rate of rental units there. Simultaneously, unsubsidized, non-voucher households re-optimize their residential decisions in response to changing rent prices and demographic compositions in their neighborhoods, leading to

[1] Notable examples in this area of research include Aliprantis and Richter (2020); Chetty and Hendren (2018); Chetty et al. (2016); Chyn (2018); Damm and Dustmann (2014); Katz et al. (2001); Kling et al. (2007, 2005); Leventhal and Brooks-Gunn (2003); Ludwig et al. (2013).

[2] I present an example of such segregation in Dallas-Plano-Irving, TX Metro Division, the area of interest for this research, in Appendix C. The number of households under the poverty line is generally high in low-quality neighborhoods as measured by the median contract rent, and vice versa.

[3] There are well-documented mechanisms through which such segregation pattern comes about, 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, 2019; Ioannides, 2011).

a new sorting/segregation pattern. This change in the equilibrium potentially affects non-voucher households' welfare. While the immediate impact on the direct recipients of the policy is well established, little is known about how the SAFMR reshapes the residential equilibrium.[4] This paper uncovers the broader impact of the program that goes beyond the first-order benefits accrued by immediate beneficiaries.

The SAFMR was introduced because the fair market rent (i.e. the maximum rental subsidy amount) set under the traditional design of the HCVP significantly prevents voucher families from residing in high-opportunity neighborhoods.[5] Under the original design, it sets the fair market rent (FMR) to the 40th percentile of the distribution of gross rents within a metropolitan area. A single metro-wide subsidy cap mechanically makes most of the rental units in high-rent, high-opportunity neighborhoods ineligible for voucher households. In other words, rental units that are priced under the cap will be heavily concentrated in low-rent, low-opportunity neighborhoods, limiting voucher households' ability to live in high-opportunity neighborhoods. Following a lawsuit that ruled the metro-wide cap makes it difficult for voucher households to access high-rent neighborhoods, HUD piloted the SAFMR that required FMRs to be set by neighborhood (defined using ZIP code), in the Dallas metropolitan area in 2011 followed by 23 additional metropolitan areas in 2018.[6,7] This design, in turn, mechanically increased the number of eligible rental units in high-opportunity neighborhoods as higher FMRs are set for high-rent neighborhoods and lowered the financial barriers for low-income households to enter these areas.

In essence, the SAFMR catalyzes a more *polarized* residential equilibrium in terms of rent prices: the demand shift coming from voucher households makes expensive, high-opportunity neighbor-

[4]Early evidence suggests that the SAFMR succeeded in moving voucher households out of low-opportunity neighborhoods and into higher-opportunity neighborhoods (Collinson and Ganong, 2018; Dastrup et al., 2018; Eriksen et al., 2023). The landlords, on the other hand, strategically changed the rental prices to charge more than the market rate to voucher tenants (Collinson and Ganong, 2018; Desmond and Perkins, 2016; McMillen and Singh, 2020).

[5]Other factors that prevent voucher households from moving to higher opportunities include sorting based on preference as low-opportunity neighborhoods tend to offer amenities valuable to low-income households, such as shorter commutes and racial diversity, (Bergman et al., 2019; Galiani et al., 2015) and avoiding voucher tenants by landlords actively screening voucher status (Aliprantis et al., 2022; Cunningham et al., 2018; Geyer, 2017; Phillips, 2017).

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

[7]Five other Public Housing Authorities (PHAs), including Chattanooga Housing Authority in Tennessee, Housing Authority of Cook County in Illinois, Housing Authority of the City of Laredo in Texas, Housing Authority of the City of Long Beach in California, and Town of Mamaroneck Housing Authority in New York, participated in the demonstration of the SAFMR in 2012 (Dastrup et al., 2018).

hoods more expensive while making cheap, low-opportunity neighborhoods cheaper. On the other hand, it leads to a more *egalitarian* residential equilibrium in terms of income compositions as low-income households move to high-opportunity neighborhoods and high-income households substitute their residential choices to lower-opportunity neighborhoods than they would have absent the policy. Given the inherent correlation between income and race, this re-location pattern implies an egalitarian residential equilibrium in terms of racial compositions as well, fostering greater income and racial integration across and within neighborhoods.

This SAFMR-induced equilibrium has potentially heterogeneous welfare impacts on high- and low-income households that are not part of the voucher program. The increased housing costs in high-opportunity neighborhoods are associated with negative welfare consequences for high-income households, the typical residents of those areas. On the other hand, low-income households with the majority of them living in low-opportunity neighborhoods indirectly benefit from this policy as they face lower living costs. The SAFMR has the potential to not only give better access for some of the low-income households in the voucher program to move to higher-opportunity neighborhoods but also allow low-income *non-voucher* households to live in more affordable homes.

Initial empirical findings underscore the effectiveness of the SAFMR in increasing voucher usage in high-opportunity neighborhoods. Notably, the number of voucher households in high-opportunity neighborhoods increased by more than 40% by 2017 with a trend that continues to rise. In some Census tracts, for example, the number of voucher households shot up from nearly 0 to well over 200 in a decade. The results suggest that there indeed has been a re-shifting of the voucher population across neighborhoods within the Dallas metropolitan area with a significant demand flowing into high-opportunity neighborhoods. This inevitably changed the landscape of the housing market and neighborhoods.

Changes in rent prices and demographic compositions were in line with the expectations. Rent prices in high-opportunity neighborhoods experienced about a 4% increase. On the other hand, rent prices in low-opportunity neighborhoods declined about 4%, suggesting a more polarized equilibrium has formed in terms of rent prices. In contrast, the policy has led to a more egalitarian residential equilibrium in terms of income and racial composition. I first find that the share of low-income households increased in high-opportunity neighborhoods and decreased in low-opportunity neighborhoods, a consistent result with voucher households' movements. However, the opposite was observed in the share of middle-income households: their share decreased in high-opportunity neighborhoods and increased in lower-opportunity neighborhoods. This result was mirrored in racial demographics as well, with an increase in the Black population and a decrease in the white population in high-opportunity neighborhoods, and vice versa in low-opportunity neighborhoods.

To examine the welfare impact of this new equilibrium, I develop and estimate a household sorting model featuring endogenous rent prices and demographic compositions of neighborhoods with a calibrated housing supply function. With the estimated model, I first find that the introduction of SAFMR led to a modicum of welfare loss for high-income non-voucher households accounting for roughly 0.1% of their annual income. This result is consistent with the observed rent increases in high-opportunity neighborhoods. In contrast, with declines in rent prices in low-opportunity neighborhoods, a substantial welfare gain followed for low-income non-voucher households, especially in the first income-quartile group, accounting for 0.6% of their annual income. While SAFMR helped a small fraction of low-income households move to higher-opportunity neighborhoods through vouchers, it also made housing more affordable for other low-income households without vouchers, albeit at a slight welfare loss to wealthier households.

However, assessing the welfare impact of instituting SAFMR in a world with metro-level FMR (MFMR) portrays only half the picture, as it misses the welfare cost of the HCVP itself. I examine the welfare effects of implementing the MFMR and SAFMR versions of the voucher program starting from a world without either. I find that instituting the voucher program itself–regardless of the design of FMR–had a substantial welfare loss to the households, especially for those in the lowest income-quartile group. However, instituting MFMR led to a much greater welfare loss for the non-voucher households in the lowest income-quartile group accounting for 2.92% of their annual income, whereas having a ZIP code-level version almost halves the welfare loss for them to 1.52%. The difference in welfare arises because the MFMR mechanically concentrates the demand for housing from voucher households in low-opportunity neighborhoods, whereas the SAFMR redirects some of that demand to higher-opportunity neighborhoods, splitting the welfare burden more evenly across the income distribution.

The two welfare results above suggest that a policymaker faces a stark trade-off when considering the HCVP. On one hand, the voucher subsidy allows a small portion of low-income households to gain access to higher-opportunity neighborhoods. However, it will also inevitably increase the rent prices in low-opportunity neighborhoods associated with the increase in demand from voucher households in those areas. This price increase ultimately hurts the welfare of the low-income households residing there, the very group the voucher program is designed to help. If the policymaker deems it more beneficial to implement the voucher program to increase access to opportunity for some of the low-income households, then the small area version of it may be more desirable as the welfare cost is split more evenly across the income distribution of an area.

This paper contributes to the existing literature in three significant ways. First, it contributes to the broad literature examining the effects of various housing policies on local characteristics and the general equilibrium. Studies such as Baum-Snow and Marion (2009); Davis et al. (2023); Diamond and McQuade (2019); Eriksen and Rosenthal (2010) analyze the impact of affordable housing construction through the Low Income Housing Tax Credit (LIHTC). Diamond et al. (2019) investigate the consequences of rent control on tenant and landlord behavior, while Autor et al. (2014, 2017) study the spillover effects of elimination of rent control on housing markets. Ali and Raviola (2023) study the effect of Community Land Trusts buying and reselling homes at affordable prices to households on neighborhood compositions. More recently, Almagro et al. (2023) examine the impact of public housing demolitions in Chicago on neighborhood characteristics and welfare of different demographic groups. Related to voucher policies are studies by Davis et al. (2021) and Galiani et al. (2015), which focus on various implications of voucher usage when households are restricted to use vouchers in only certain neighborhoods. In contrast, I study a setting where voucher households have freedom in selecting neighborhoods and enhanced access to high-opportunity neighborhoods, thanks to the new design of the voucher program.

Second, it expands the growing body of research on the Housing Choice Voucher Program, specifically in the context of the Small Area Fair Market Rents. Previous studies have primarily focused on the immediate beneficiaries of the policy, namely voucher households and the landlords who rent to them. Some studies have examined voucher take-up rates and sorting patterns among voucher households (Collinson and Ganong, 2018; Dastrup et al., 2019; Horn et al., 2014; Ingrid Gould Ellen and Harwood, 2023; Mazzara and Knudsen, 2019; Vincent Reina and Bostic, 2019). Others have investigated how landlords respond to potential voucher tenants in terms of pricing and discrimination (Aliprantis et al., 2022; Collinson and Ganong, 2018; Eriksen and Ross, 2015; Olsen, 2019; Phillips, 2017). Building upon this literature, this study explores how the actions of voucher households can initiate a ripple effect on the local economy, influencing rental prices and demographic compositions across neighborhoods through the sorting behavior of both voucher and non-voucher households. Most importantly, I assess the unintentional welfare implications of this new equilibrium on non-voucher households.

Lastly, this research contributes to a broad literature that uses structural models of neighborhood choice to study household sorting and welfare (Bayer et al., 2007; Bayer and McMillan, 2005; Bayer et al., 2016, 2004; Davis et al., 2023; 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). My paper uses the new design of the housing voucher program as an exogenous variation to identify household preferences.

The remainder of the paper proceeds as follows. Section 2 lists the institutional background of the 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 the 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 the HCVP and SAFMR on the local economy that goes beyond the immediate recipients of the policy.

2 Institutional Background

The Housing Choice Voucher Program (HCVP), also commonly known 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 2.3 million low-income families with affordable homes in 2021.[8] HUD allocated $32.1 billion to the HCVP in 2023 out of the total budget of $71.9 billion requested by the President's Budget, making it the largest federally run housing subsidy program in the U.S.[9]

[8] https://www.huduser.gov/portal/datasets/assthsg/statedata98/descript.html
[9] https://www.hud.gov/sites/dfiles/CFO/documents/2023_BudgetInBriefFINAL.pdf

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).[10] HUD first calculates the FMR based on the 40th percentile of the gross rent for each region and bedroom size. The PHAs then decide the exact payment standards to fall anywhere between 90% and 110% of the HUD-proposed FMRs at their own discretion, taking local housing market conditions into consideration.

In theory, voucher households have the freedom to locate anywhere within the metropolitan area as long as they can lease an appropriately priced unit because they are price insensitive as they pay the same amount toward rent regardless of where they choose to live. For example, a voucher household earning $1,000 per month is responsible for paying $300 towards rent as long as the rental unit they reside in is priced below the payment cap. If, for example, the cap is set at $1,300 and the rental unit that they live in is priced at $1,200, then the voucher household pays $300 and the rest of the rent ($900) will be paid by the government. However, if they opt to live in a unit that is priced above the cap, say $1,400, then the household needs to pay a total of $400 towards rent: $300 from the monthly income and $100 of the excess payment.

However, the way FMRs are traditionally designed mechanically makes finding a fitting unit in high-rent, high-opportunity neighborhoods a challenging task for voucher households. The FMRs are traditionally set for each Core Based Statistical Area (CBSA) for metropolitan areas with slight modifications based on HUD's definition of fair market rent areas.[11] The metropolitan-level design of the FMR (MFMR) oversaturates rental units available to voucher holders in low-opportunity neighborhoods, making it difficult for voucher households to find eligible units in high-opportunity neighborhoods associated with higher rents.

Following the settlement of the Walker v. U.S. HUD lawsuit, which ruled that the use of MFMR restricted voucher families from residing in predominantly white, high-rent neighborhoods, HUD implemented the Small Area Fair Market Rents (SAFMR) in the Dallas metropolitan area.[12] The SAFMR sets the FMR at a much more geographically granular level–the ZIP code–than the MFMR. To determine the ZIP code-level FMRs, HUD multiplies the rental rate ratio in each ZIP code by

[10] 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.

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

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

the 2-bedroom FMR for the relevant Core Based Statistical Area (CBSA), where the rental rate ratio is the ratio of the median gross rent in the ZIP code to the median gross rent in the CBSA.[13] This new approach provides a more accurate reflection of the rent levels in each ZIP code and expands the pool of available homes in high-opportunity neighborhoods for voucher households.

HUD expanded the mandatory use of SAFMR to 23 additional metropolitan areas across the U.S. in 2018. These areas were chosen based on the following five metropolitan 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 the 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 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.[14] The list of metropolitan areas that met all five criteria is presented in Table 1.

3 Expected Long-Run Effects on Residential Equilibrium

The expected effect of the SAFMR is manifested through the relocation decisions of both voucher and non-voucher households. In this section, I sequentially illustrate the mechanisms through which the policy affects the rental market and residential equilibrium and what the predicted effects are in long-run equilibrium. To fix ideas, I assume there is a fixed housing supply and a fixed number of households in a metropolitan area throughout the illustration in this section.

The direct effect of the policy is realized through the movement of voucher households. As the policy allows more rental units to be voucher-eligible, the voucher households, particularly newcomers to the program, move into high-opportunity neighborhoods (Eriksen et al., 2023). This surge in demand precipitates an increase in rent prices in the affected neighborhoods. On the

[13] Further explanations on how the ZIP code-level FMRs are constructed can be found in Section II of Docket No. FR–5413–N–01.

[14] HUD initially selected 31 metropolitan areas that met all five criteria. However, in practice, the policy became effective only in 23 (out of the initial 31) metropolitan areas. The final selection rule of the 23 metropolitan areas still remains in the dark with no clear explanations offered from HUD.

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

HUD Metropolitan Area	# Vouchers
Metros with SAFMR in Place in 2011	
Dallas-Plano-Irving, TX Metro Division	28,135
Metros with SAFMR in Place in 2018	
Atlanta-Sandy Springs-Marietta, GA HUD Metro FMR Area	28,697
Bergen-Passaic, NJ HUD Metro FMR Area	11,503
Charlotte-Gastonia-Rock Hill, NC-SC HUD Metro FMR Area	7,951
Chicago-Joliet-Naperville, IL HUD Metro FMR Area	62,472
Colorado Springs, CO HUD Metro FMR Area	2,957
Fort Lauderdale-Pompano Beach-Deerfield Beach, FL Metro Division	10,486
Fort Worth-Arlington, TX HUD Metro FMR Area	12,620
Gary, IN HUD Metro FMR Area	3,305
Hartford-West Hartford-East Hartford, CT HUD Metro FMR Area	12,831
Jackson, MS HUD Metro FMR Area	4,742
Jacksonville, FL HUD Metro FMR Area	5,872
Monmouth-Ocean, NJ HUD Metro FMR Area	7,811
North Port-Bradenton-Sarasota, FL MSA	2,592
Palm Bay-Melbourne-Titusville, FL MSA	2,565
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD MSA	32,631
Pittsburgh, PA HUD Metro FMR Area	15,739
Sacramento–Arden-Arcade–Roseville, CA HUD Metro FMR Area	12,672
San Antonio-New Braunfels, TX HUD Metro FMR Area	14,633
San Diego-Carlsbad-San Marcos, CA MSA	27,970
Tampa-St. Petersburg-Clearwater, FL MSA	16,456
Urban Honolulu, HI MSA	4,146
Washington-Arlington-Alexandria, DC-VA-MD HUD Metro FMR Area	32,109
West Palm Beach-Boca Raton-Delray Beach, FL Metro Division	6,058
Metros Selected but Never Mandated	
Nassau County-Suffolk County, NY Metro Division	11,593
New York, NY HUD Metro FMR Area	119,362
Oakland-Hayward-Berkeley, CA Metro Division	28,355
Oxnard-Thousand Oaks-Ventura, CA MSA	5,612
San Jose-Sunnyvale-Santa Clara, CA HUD Metro FMR Area	14,307
Tacoma-Lakewood, WA Metro Division	5,341
Virginia Beach-Norfolk-Newport News, VA-NC HUD Metro FMR Area	12,291

Notes: The table above lists the HUD metropolitan areas that (1) adopted the 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. 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 contrary, the departure of low-income households from low-opportunity neighborhoods results in a decrease in prices there. This direct effect on rent prices causes the rent prices to go up in high-rent, high-opportunity neighborhoods and down in low-rent, low-opportunity neighborhoods.

The indirect effects of the policy are then manifested through the re-sorting of the non-voucher households who respond to changes in neighborhoods. Increased housing prices make it more difficult for these households to afford a place in higher-opportunity neighborhoods. Moreover, changes in the demographic characteristics of their potential neighbors (i.e. more minority and/or low-income households) may also impact their relocation decisions (Bayer et al., 2022). Both factors displace incumbent households in high-opportunity neighborhoods and deter potential in-migrants who would be able to afford such neighborhoods in the absence of the policy.

The subsequent residential re-optimizations of these households primarily take two forms. A small fraction of the affected households may opt to pay a premium to reside in more expensive units that are not attainable by voucher households in high-opportunity neighborhoods. This will marginally raise the rent prices in the upper distribution of rental units in these neighborhoods. Other households, however, are likely to seek housing in lower-opportunity neighborhoods that are within their affordability range. Such moves will again exert pressure on housing prices in lower-opportunity neighborhoods, particularly at the upper end of the rent distributions in these areas. In aggregate, this force will further make high-opportunity neighborhoods more expensive and marginally increase rent prices in lower-opportunity neighborhoods.

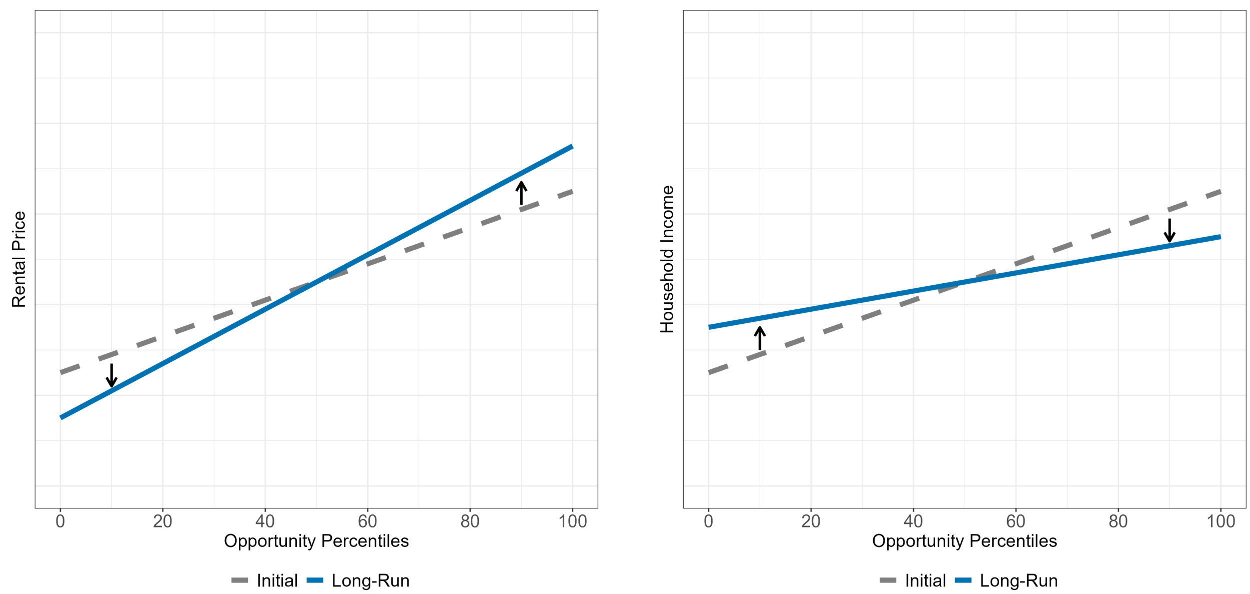
I summarize the combined effects on rent prices in the left panel of Figure 1 where I plot hypothetical rent price gradients with respect to neighborhoods in opportunity percentiles as measured by the level of FMR of neighborhoods.[15] The initial residential equilibrium prior to policy implementation is pictured in a gray dashed line. The positive slope indicates that the rent level of a neighborhood is higher in higher-opportunity neighborhoods. The policy leads to an increase in rent prices in high-opportunity neighborhoods, whereas the prices decline in low-opportunity neighborhoods. These forces tilt the price gradient counterclockwise in the long run, suggesting that the SAFMR creates a polarized rent equilibrium. It makes expensive neighborhoods more expensive and cheap neighborhoods cheaper.

In contrast, the effect of the policy on income composition across neighborhoods portrays a

[15] I provide an empirical analog of the change in the equilibrium in Appendix C.

Figure 1: Expected Effects of SAFMR on Residential Equilibrium

(a) Rent Price Gradients (b) Household Income Gradients



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. The gradients induced by the direct effect of the policy change are plotted in dashed yellow lines. The initial gradients are plotted in dashed-gray lines. The expected long-run equilibrium is depicted in solid-blue lines.

different long-run equilibrium. The direct effect is that the policy increases the share of low-income households in traditionally high-income, high-opportunity neighborhoods. The indirect effect follows that incumbent high-income households who are displaced by voucher households re-optimize their residential choices and substitute to lower-opportunity neighborhoods than they would have in the absence of the policy. This effect is manifested through the household income gradient tilting clockwise as shown in the right panel of the figure. A flatter slope compared to the initial equilibrium suggests the SAFMR potentially yields a more egalitarian equilibrium in terms of income diversity across and within neighborhoods.

Given the strong correlation between income and race in the U.S., this long-run equilibrium implies a more racially diverse household distribution within neighborhoods as well. The inflow of minority households to higher-opportunity neighborhoods and the outflow of non-minority households to lower-opportunity neighborhoods leads to a shift in racial demographics. Traditionally non-minority dominant neighborhoods will see an increase in the share of minority households, and minority-dominant neighborhoods will experience a surge in the share of non-minority households. Thus, the policy contributes to creating a more racially egalitarian equilibrium with reduced residential segregation.

4 Data

The primary data used in this research are from the publicly available ZIP code-level aggregate statistics from the 5-year American Community Survey (ACS), spanning from 2007-2011 to 2015-2019, provided by the National Historical Geographic Information System (NHGIS) (Manson et al., 2022). The main survey estimates used in the analysis include the 25th-quartile, median, and 75th-quartile contract rents, as well as the number of households in each zip code by race. Tract-level aggregate statistics from the 5-year ACS from 2005-2009 to 2015-2019 ACS are also employed whenever the analysis is performed at the tract level. To understand the distribution of household income in each zip code, I supplement the ACS data with the zip code-level income data from the Statistics of Income Division of the Internal Revenue Service (IRS). In addition to the neighborhood-level data listed above, I use the household-level data on rents that are obtained from the Integrated Public Use Micro Data Series USA (IPUMS USA) (Ruggles et al., 2022), specifically from the 2000 5% sample and 1-year ACS from 2006 to 2021, the latest one available to date. They are used to characterize the distributions of rents in each metropolitan area over time.

Data on both metropolitan- and ZIP code-level FMRs come from HUD. For each fiscal year, HUD makes FMR values publicly available for all metropolitan areas, counties, and ZIP codes in the U.S. This means that the FMRs are calculated for all geographical denominations for all areas regardless of whether the FMRs are implemented at the metropolitan or ZIP code level. Such *hypothetical* FMRs provide guidance on categorizing neighborhoods by opportunity types described later in Section 4.1.

In addition, I obtain publicly available data on the number of voucher households in each neighborhood from HUD, called Picture of Subsidized Households (PoSH), from 2007 to 2022. The tract-level PoSH data spans the entirety of this period, although the geographic definition of Census tracts shifts from 2000 to 2010 in 2012. The zip code-level data is available from 2017 to 2022. I standardized the geographic definition of tracts to the 2010 definition and created pre-2017 zip code-level data by harmonizing the tract-level data accordingly. I discuss this process in more detail in Appendix A. Furthermore, I supplement my analysis with the PoSH data at the core-based statistical area (CBSA) level to summarize the aggregate level change in voucher usage.

To document the micro-movements of households within and across neighborhoods, I use data from InfoUSA's Residential Historical Database. InfoUSA is a proprietary data set that tracks 120 million households in the U.S. from 2006 to 2020 and includes information on residential location, estimated household income and wealth, renter/owner status, and ethnicity. By using the exact address information, I can identify the residential locations of households before and after the policy intervention over time.

4.1 Defining Opportunity Status for Each Neighborhood

As discussed in Section 2, HUD recommends FMRs for each ZIP code, and the PHA has the discretion to choose the payment standards that fall within 90% and 110% of the HUD-proposed FMRs. Although the FMRs for all ZIP codes in the United States are publicly available from HUD, the exact payment standards that PHAs set are challenging to observe as they were locally distributed through mail or published on each PHA's website in the past with no available web archive. Given this constraint, I define the opportunity status of each ZIP code based on the widely and publicly available FMRs from HUD.

Throughout the paper, I define ZIP codes as *high-opportunity* ZIP codes if their new ZIP code-level FMRs in 2011 at the lower bound (i.e., 90% of the HUD-published value) are greater than the traditional Dallas-wide FMR defined for 2011. This suggests that these high-rent ZIP codes experienced a significant and positive change in payment standards following the implementation of the SAFMR, opening up a lot of rental units to be voucher-eligible. In contrast, *low-opportunity* ZIP codes are those where the upper bound of the ZIP code-level FMRs is less than that of the metropolitan area. These low-rent areas go through significant and negative changes in the FMR, reducing the number of voucher-eligible units. The remaining ZIP codes where the metropolitan-level FMRs fall between the lower and upper bounds of the new ZIP code-level FMRs are designated as *mid-opportunity* ZIP codes. These consist of neighborhoods with little to no change in the number of voucher-eligible units, as the SAFMR had minimal impact on the new FMRs set.

In my research context, the word "opportunity" simply classifies ZIP codes into high-, mid-, and low-rent ZIP codes in a given metropolitan area. This closely aligns with the definition of "opportunity" used in recent work by Aliprantis et al. (2022) where they define "opportunity landlords" as landlords operating in high-rent neighborhoods. Although it does not necessarily capture the intergenerational mobility rate of a neighborhood as in Chetty et al. (2016) or the low-poverty rate as in the Moving to Opportunity (MTO) program that is more typically used in the literature, I show that the correlations between these measures are high in Appendix C. Thus, the implications will remain valid under different definitions of opportunities.

The most natural definition of "neighborhoods" is ZIP codes in this context. However, depending on the analytical context and data availability, the word "neighborhoods" will be used flexibly throughout the paper to account for either ZIP codes or Census tracts. I will mention explicitly the definition I am referring to in each context throughout the paper. There is one caveat of defining tracts as neighborhoods: assigning opportunity status to each tract is complicated as the FMR (and payment standards alike) are assigned based on ZIP codes and multiple tracts can belong to one or more ZIP codes (and vice versa). Thus, establishing a criterion is required. I define a tract as a high-opportunity tract if the majority of the tract, based on the residential ratio, is part of a high-opportunity ZIP code. Mid- and low-opportunity status are defined similarly but with a mid- or low-opportunity ZIP code as a reference.

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 2. 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 house-

Table 2: 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)
Voucher Households[b]	37	38	15	24	39	37	69	61
	(66)	(72)	(27)	(45)	(53)	(58)	(105)	(110)
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.

holds 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.

5 Empirical Analysis

5.1 Change in Voucher Take-ups

I first revisit earlier findings that confirm an increase in the voucher take-ups in high-opportunity neighborhoods in Dallas following the introduction of SAFMR. The analysis utilizes a standard difference-in-differences framework, comparing the number of voucher take-ups in neighborhoods in Dallas with those in neighborhoods in metropolitan areas that were selected to adopt the SAFMR later in 2018.[16] The specification is as follows:

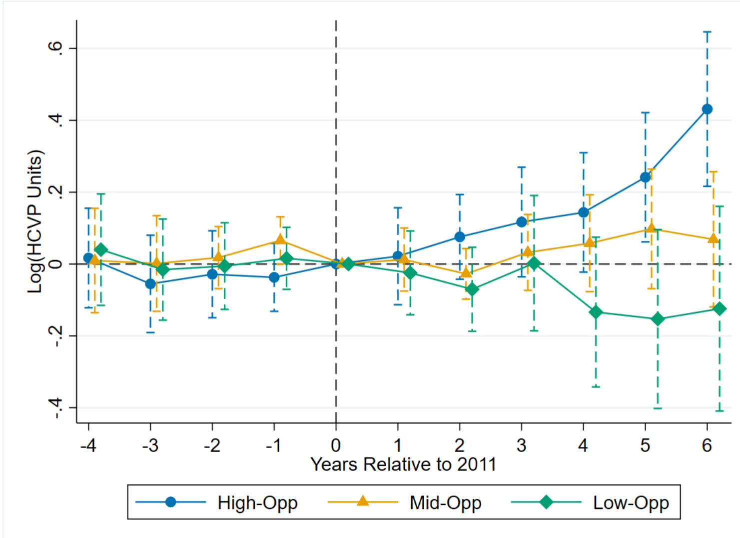
$$Y_{jt} = \alpha_j + \alpha_t + \sum_{\tau=-4}^{6} \beta_\tau \times \mathbb{I}_{jt}[t - t^* = \tau,\, m(j) = 1] + \varepsilon_{jt} \tag{1}$$

where Y_{jt} is the log number of voucher households living in ZIP code j in year t, with α_j and α_t serving as neighborhood- and year-fixed effects, respectively. The indicator variable turns on if the observation pertains to τ-years before or after relative to the treatment year t^* (i.e. 2011) and if the neighborhood j is part of Dallas (i.e. $m(j) = 1$). β_τ are the parameters of interest, and its coefficient in the year 2011 (indexed by 0) is normalized to 0. Note that my analysis concludes in 2017 (indexed by 6) because the control metropolitan areas are no longer a valid control group as they adopted the same policy in 2018. The equation is estimated separately for each neighborhood opportunity type and the event-study estimates are presented in Figure 2.

There is an evident increase in voucher utilization in high-opportunity neighborhoods post-2011 as shown by the blue circles in the figure. The number of voucher households in these neighborhoods rose by 42% by 2017 which aligns with the previous findings in the literature. This increase is gradual because the households who are more likely to exploit the new design of the

[16] The control group includes all HUD metropolitan areas listed in Table 1, except for the Dallas-Plano-Irving, TX Metro Division itself.

Figure 2: 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. 95% confidence intervals are shown in the figure.

policy and move to high-opportunity neighborhoods are those newly enrolled in the HCVP. Existing households in the program are likely to respond more slowly due to potential higher moving costs and established social ties in their current neighborhoods.

Mid-opportunity neighborhoods exhibited stable voucher take-up rates over time as depicted by yellow triangles in the figure. This is expected because of the minimal difference between the old metropolitan-level and the new neighborhood-level FMRs. As the availability of rental units in these neighborhoods remains unchanged, the voucher households are expected to behave in a similar manner as before. On the other hand, low-opportunity neighborhoods experienced an 18% decline in the number of voucher households, although the estimates are statistically insignificant.

Collectively, the findings suggest a significant re-distribution of the voucher population within the Dallas metropolitan area following the policy change. This shift in the voucher population is likely to influence rental prices and demographic compositions in different neighborhoods within the metropolitan area through the indirect effects manifested by the sorting of non-voucher households.

5.1.1 Voucher Concentration and Neighborhood Characteristics

The policy enabled low-income voucher households to move to high-opportunity neighborhoods. However, it is overly simplistic to assume the increase in the voucher population to be uniform across all high-opportunity neighborhoods. It is more realistic to reason that these voucher households would migrate to neighborhoods that align more closely with their inherent preferences–areas that perhaps offer better access to public transportation and areas with higher shares of minority households that meet their racial homophily preferences (Bayer and McMillan, 2005).

This is well manifested in the map in Figure 3. The left panel of the figure plots Census tracts in the Dallas metropolitan area with their respective opportunity status. High-opportunity neighborhoods are mainly concentrated in the upper-west quadrant of the metro area. Meanwhile, most of the mid-opportunity neighborhoods encircle the city center, whereas low-opportunity neighborhoods are distributed in the urban core and the peripheral regions to the south and east. The right panel of the figure plots the change in the number of voucher households in each tract from 2010 to 2022. Within the cluster of high-opportunity neighborhoods, it is evident that the increase in the number of voucher households is not uniformly dispersed. Instead, specific clusters of tracts emerge as focal points of the voucher population.

To see more explicitly the high-opportunity neighborhoods where voucher households are more likely to move to, I estimate the following

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

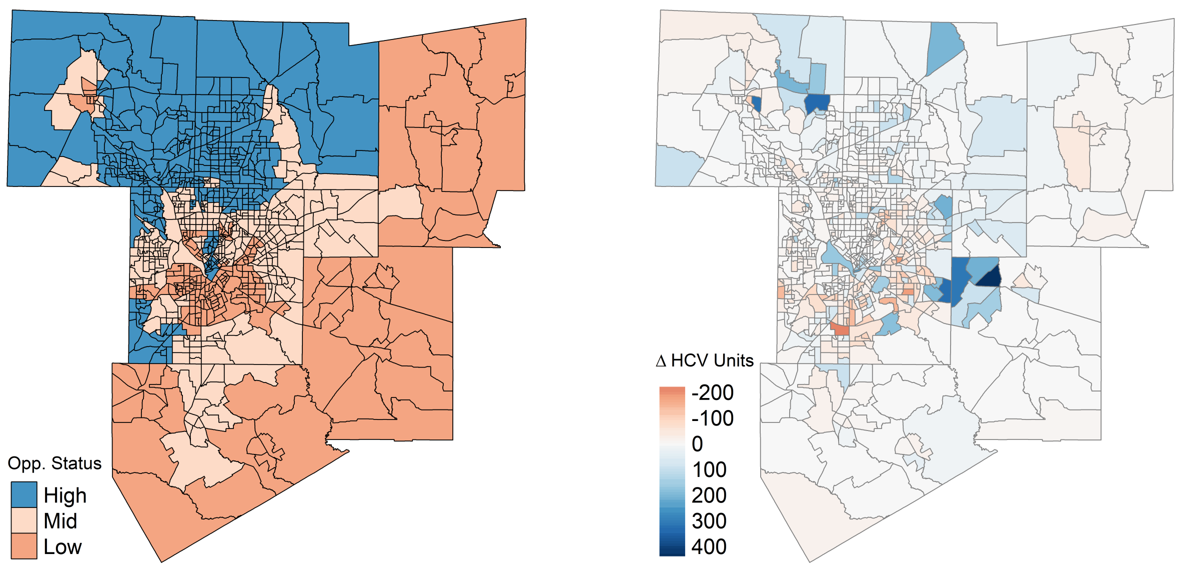
where the dependent variable is the change in the number of voucher households from 2010 to 2019 in each Census tract j. This is regressed on the baseline characteristics of each tract in the year 2010 to capture the correlations of voucher concentration and various neighborhood amenities. The neighborhood characteristics include the newly implemented ZIP code-level FMR ($\text{SAFMR}_{j,2010}$), the share of minority households ($M_{j,2010}$) inclusive of both Black and Hispanic households, and the share of workers who commute via public transportation ($PT_{j,2010}$) serving as a proxy for how easy it is for people in the neighborhood to access public transportation.[17]

[17] The baseline characteristics indicated by the year subscript 2010 come from the tract-level 2006-2010 ACS data, except for $\text{SAFMR}_{j,2010}$ which are the newly assigned ZIP code-level FMR in *2011*. I use the 2010 subscript to retain consistency in the empirical specification.

Figure 3: Neighborhoods in Dallas Metropolitan Area and Voucher Usage

(a) Opportunity Status

(b) Change in Voucher Households (2010-2022)



Notes: The figures above show maps of Census tracts in Dallas based on the 2010 geographical designation. The left panel is a map that categorizes tracts into three different opportunity statuses. The right panel depicts the change in the number of voucher households in each tract from 2010 to 2022.

Regression coefficients are presented in Table 3. In high-opportunity neighborhoods, the near-zero effect of the new FMRs suggests voucher households are largely indifferent to rent levels when considering residential locations. This is expected because voucher households pay a fixed portion of their monthly income towards rent as long as they are able to secure a residential place priced below the payment standard. Therefore, they would most like to put more weight on anything but rent prices. The positive and significant coefficient on the share of minority people indicates that voucher households, a predominantly non-white group of people, cluster in neighborhoods with higher shares of minority.[18] Furthermore, a much higher correlation coefficient for public transportation accessibility underscores the premium placed by voucher households in public transit-friendly neighborhoods. However, it is important to note that this spatial pattern could be a product of a combination of preference, discrimination, high search costs, and other frictions voucher households face. Although it is difficult to distinguish these multiple channels, the takeaway from the analysis is that there is a specific set of high-opportunity neighborhoods to which voucher households move.

[18]80% of the voucher households in Dallas in 2010 were Black and 6% of them were Hispanic.

Table 3: 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.

5.2 Change in Rent Prices

The observed uptick in voucher usage in high-opportunity neighborhoods is expected to exert upward pressure on rental prices within these areas. Conversely, reduced demand for low-opportunity neighborhoods will precipitate a decline in rent prices in these areas.

To analyze the changes in rent prices, I again adopt the difference-in-differences framework. However, as the ZIP code-level aggregate data on rents are from the 5-year ACS, I resort to the standard 2×2 form as follows:

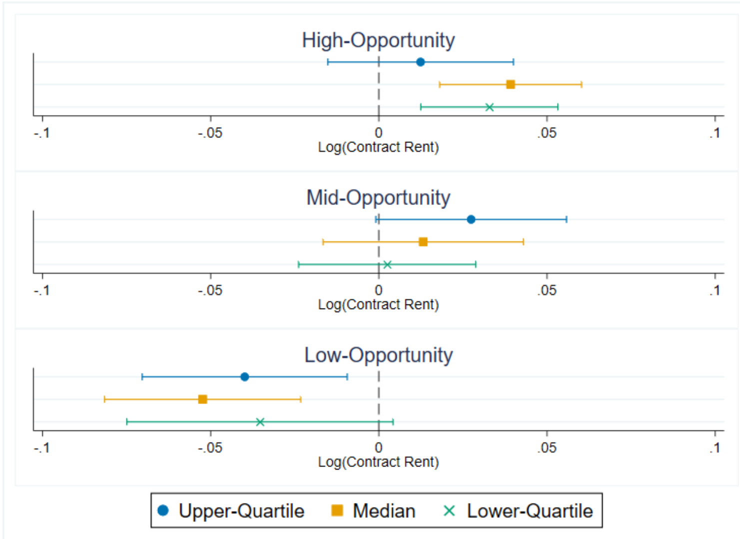
$$Y_{jt} = \alpha_j + \alpha_t + \beta D_{jt} + \varepsilon_{jt} \tag{3}$$

where Y_{jt} is the log contract rent of ZIP code j at year t.[19] D_{jt} is the standard indicator variable for being in the post-treatment period interacted with whether the neighborhood j is in Dallas or one of the control metropolitan areas. I use estimates from the 2007-2011 ACS for pre-treatment outcomes and 2013-2017 ACS for post-treatment outcomes.[20] I regress the above separately for the three neighborhood opportunity types with contract rents at three points in the distribution: lower-

[19] I am not able to control for idiosyncrasies for individual metropolitan areas as Dallas is the only treated metropolitan area in the research setting. To control for such idiosyncrasy coming from Dallas, I take out the mean effects of the three opportunity neighborhoods from the estimated β's.

[20] Ideally, one would use the 2006-2010 ACS to assess the pre-treatment values since the 2007-2011 ACS subsumes estimates from the treatment year, 2011. Unfortunately, however, the 2007-2011 ACS is the earliest survey data available at the ZIP code level.

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. 90% confidence intervals are shown in the figures.

quartile, median, and upper-quartile. A standard identification assumption follows that the housing market trends would be the same in both the neighborhoods in the Dallas metro and comparable neighborhoods in other control metros in the absence of the SAFMR. Although I cannot directly test for this trend in the pre-treatment period at the neighborhood level, I give support to this parallel trend using metropolitan-level data in Appendix C. The results for the contract rent price changes are presented in Figure 4.

The SAFMR policy led to a 3.9% and 3.3% increase in the median and lower-quartile contract rent prices, respectively, in high-opportunity neighborhoods with no significant price increase in the upper quartile. Mid-opportunity neighborhoods witnessed a 2.7% increase in the upper-quartile rent price. On the other hand, the results for low-opportunity neighborhoods paint a different picture. The policy led to a 5.2% and 4.0% decrease in contract rent prices in the median and upper quartile, respectively, with statistically insignificant change in the lower-quartile rent price.

The differential changes in the rent levels in varying opportunity neighborhoods align well with expectations as described in Section 3. Post-policy, one would anticipate the demand to increase the most at the lower end of the rent distribution in high-opportunity neighborhoods as these units become newly eligible for voucher households. Correspondingly, the demand would fall at the upper end of the rent distribution in low-opportunity neighborhoods as these units lose eligibility under the new design. Such shifts in demand cohere with the rise in prices at the lower end of the distribution in high-opportunity neighborhoods and the fall at the upper end of the distribution in low-opportunity neighborhoods.

Indirect effects are evident in non-voucher households–especially the incumbent households displaced by incoming voucher tenants in high-opportunity neighborhoods. These households are likely to reassess their residential choices, causing a demographic reshuffling across different neighborhoods. They will substitute into the next best neighborhoods, a movement well reflected by the rise in rents in mid-opportunity neighborhoods.

5.2.1 Heterogeneous Price Response

I documented above that the voucher households predominantly cluster in neighborhoods with a larger minority presence and more accessible public transportation. Such a heavy concentration of voucher households in certain parts of the area potentially leads to heterogeneous price responses across different neighborhoods in the Dallas metropolitan area.

To examine further which of the neighborhoods experienced notable fluctuations in rent values, I estimate the following

$$P_{jt} = \beta_0 + \beta_1 \text{FMR}_{jt} + \beta_2 \text{HCVP}_{jt} + \beta_3 M_{jt} + \lambda_j + \lambda_t + \varepsilon_{jt} \tag{4}$$

separately for lower-quartile, median, and upper-quartile rents as the dependent variable, P_{jt}. This analysis uses two cross-sections of the 5-year ACS, 2006-2010 and 2015-2019, as indexed by t. FMR_{jt} represents the FMR value in each tract j in year t. I rely on the metropolitan-level FMR value in 2011 to correspond with the 2006-2010 ACS data and the zip code-level FMR values in 2018 for the 2015-2019 ACS data. HCVP_{jt} is the number of voucher households living in each tract in the years 2010 and 2019. I include the tract and year fixed effects as λ_j and λ_t, respectively. Thus, this specification relates how the *changes* in neighborhood characteristics were associated with the *changes* in rent prices.

The results are presented in Table 4. For all three points in the distribution, a positive change

Table 4: Heterogeneous Price Response

	Contract Rent		
	Lower-Quartile	Median	Upper-Quartile
Fair Market Rent ($)	0.27***	0.35***	0.46***
	(0.04)	(0.04)	(0.05)
# Voucher Households	-0.30	-0.30	-0.38
	(0.20)	(0.20)	(0.26)
% Minority	-1.00	-1.98**	-3.56***
	(0.82)	(0.82)	(1.07)
Tract FE	Y	Y	Y
Year FE	Y	Y	Y
R-squared	0.87	0.91	0.90
Number of Tracts	885	885	885
Observations	1770	1770	1770

Notes: This table documents heterogeneous response of lower-quartile, median, and upper-quartile contract rents in Census tracts in the Dallas metro after the policy change. Rent values and share minority values come from 2008-2012 and 2015-2019 ACS; fair market rent values that correspond with the ACS estimates from 2008-2012 are metro-level fair market rent in Dallas in 2011 and zip code-level fair market rent values in 2018 for estimates from 2015-2019 ACS; and the number of vouchers are based on 2012 and 2019 values from the Picture of Subsidized Households, respectively.

in the FMR (i.e. higher-opportunity neighborhoods) was associated with increases in contract rent prices. This corroborates the preceding analysis that rent prices rose in high-opportunity neighborhoods and declined in low-opportunity neighborhoods. However, the second row of the table highlights that an increase in the number of voucher households was weakly associated with a decline in rent prices at the median and upper quartile. The influx of a single voucher household into a neighborhood was associated with an approximate decline of half a dollar in the rent price. Analogously, the third row shows an increase in the share of minority households was associated with a decline in median and upper-quartile rent prices–a percent increase in minority share equates to a decline in rent prices from $1.00 to $3.56.

Given the findings, there are two pivotal forces affecting rent prices. The first is the classical demand effect where an increase in demand simply triggers a surge in prices. The other is the compositional effect. It underscores the potential perceived disadvantages of low-income and minority demographics in higher-opportunity neighborhoods, which inversely affect rent prices. In other words, low-income and minority neighbors are deemed as disamenities to households living in high-opportunity neighborhoods.

Although decomposing the two effects is out of the scope of this paper, the empirical finding suggests that the increase in rents within high-opportunity neighborhoods is predominantly fueled by incumbent high-income households who migrate to and put pressure on rent prices in other high-opportunity neighborhoods that are relatively unoccupied by voucher households. The price hike in high-opportunity neighborhoods is mostly due to the demand effect from non-voucher households, whereas the average effects are muted by the compositional effect from neighborhoods experiencing a surge in the number of voucher households.

5.2.2 Supplementary 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).[21] However, the distributional synthetic control approach 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 the 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

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

represent gross rent prices in each metropolitan area at different quantiles.[22] 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 minimization problem.

$$\overrightarrow{\lambda}^*_t = \underset{\overrightarrow{\lambda} \in \Delta^M}{\operatorname{argmin}} \int_0^1 \left| \sum_{m=2}^{M+1} \lambda_m F^{-1}_{Y_{mt}}(q) - F^{-1}_{Y_{1t}}(q) \right|^2 dq \tag{5}$$

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

[22] 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.

present in 2010.[23] 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 5. 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 (5) and that the synthetic Dallas has been accurately constructed.

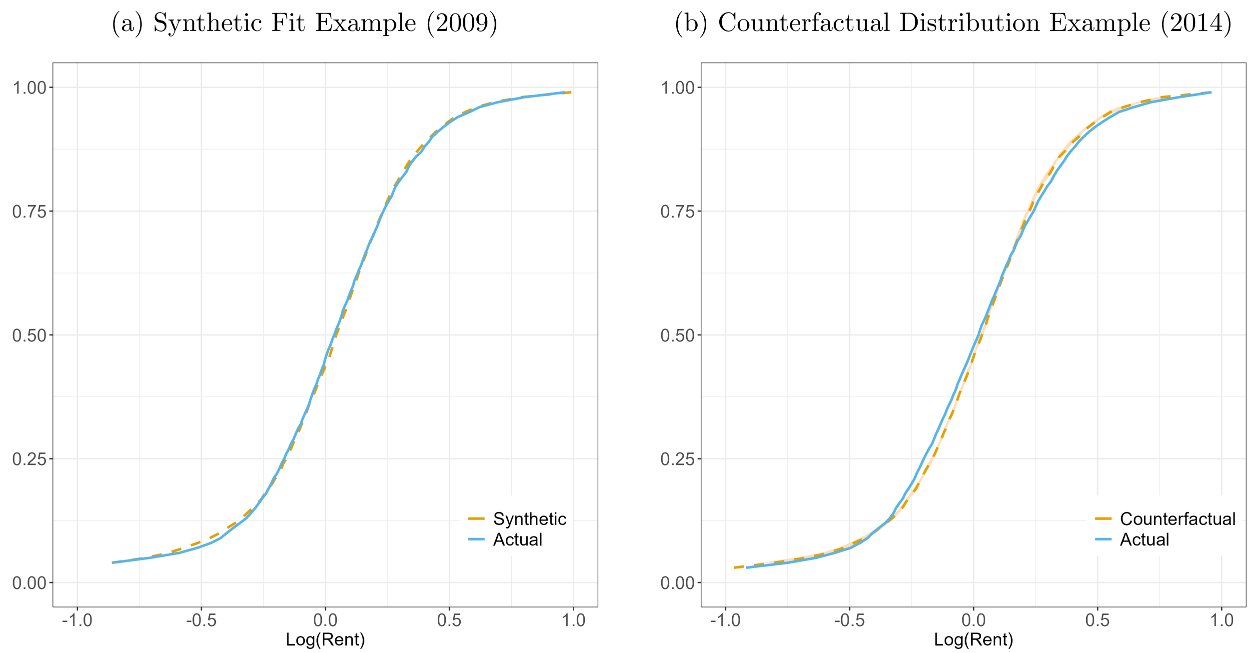
The right panel of Figure 5 displays the counterfactual distribution of rents in synthetic Dallas (represented by the dashed-orange line) and the actual rent distribution in Dallas (depicted by the solid blue line) for one of the post-treatment years (2014) as an example. The counterfactual distribution embodies the cumulative distribution function of gross rents that would have been in place in Dallas had the 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 the 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.

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 6.[24] 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.

[23] 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.

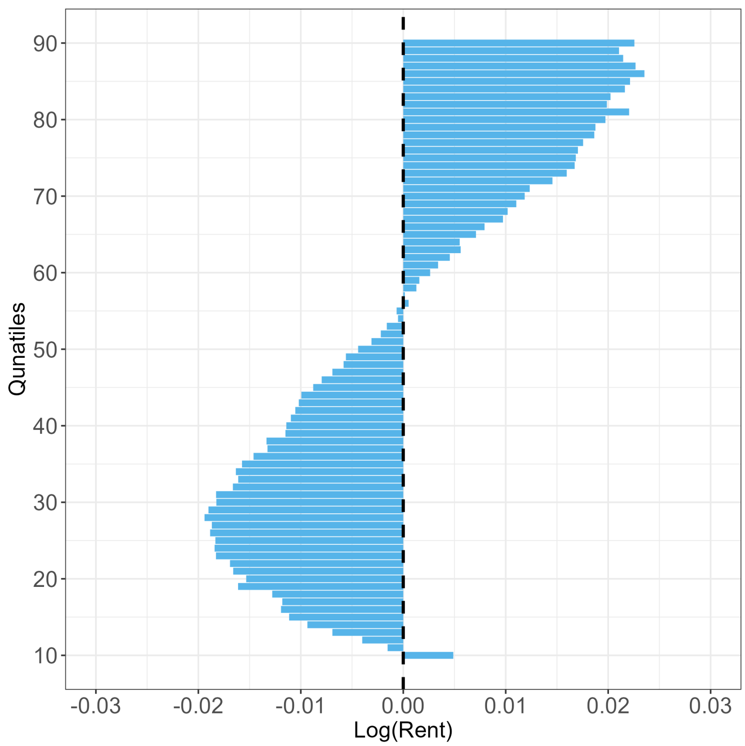
[24] Note that I only display treatment effects from the 10th to the 90th quantile points as the distributional synthetic control match tends to underperform in matching the extreme-low and upper ends of the distributions.

Figure 5: 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, $\overrightarrow{\lambda}^*$.

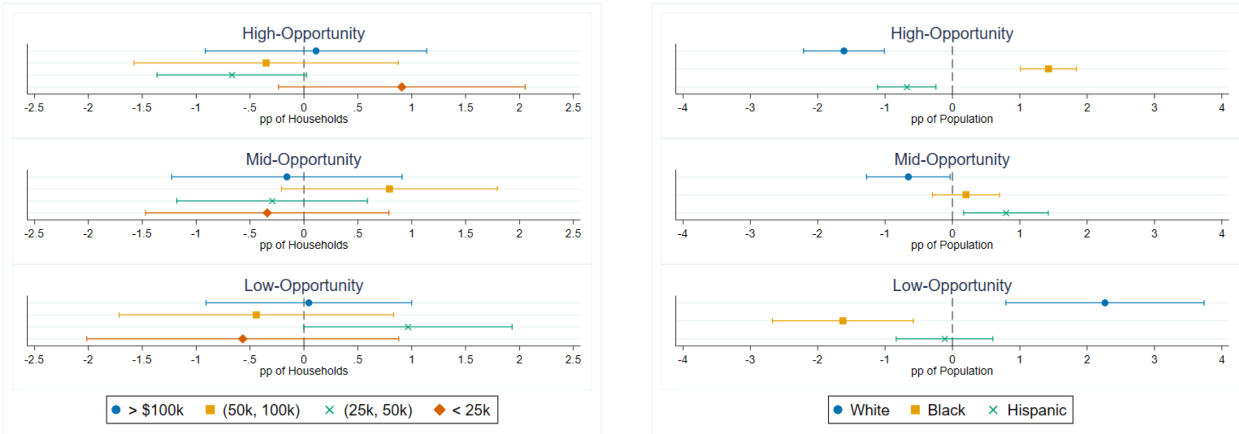
Figure 6: Distributional Synthetic Control Treatment Effects Summarized



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 7: 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. 90% confidence intervals are shown in the figures.

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.

5.3 Change in Income and Racial Compositions

In this section, I evaluate how the demographic compositions of neighborhoods changed following the SAFMR. Demographic shifts are expected as the policy channels low-income households into high-opportunity neighborhoods, which could in turn trigger a re-sorting of households. To analyze this, I estimate Equation (3) again, this time with shares of various income and racial groups as outcome variables.[25] The resulting estimates are shown in Figure 7.

The left panel shows how income compositions have evolved in different opportunity neighbor-

[25] For the income distribution analysis, I use the Statistics of Income from the IRS in 2010 for pre-treatment data and 2017 for the post-treatment data. I use the same ACS data for both the pre- and post-treatment years for the racial composition results.

hoods following the policy.[26] I first highlight the change in the share of households whose adjusted gross income is less than $25,000. Note that this group subsumes voucher households. Although establishing statistical significance is difficult given the number of ZIP codes I am working with, the point estimates are consistent with low-income voucher households taking vouchers to high-opportunity neighborhoods. The share of households with income less than $25,000 decreased in mid- and low-opportunity neighborhoods by 0.34 and 0.57 percentage points, respectively, while increasing in high-opportunity neighborhoods by 0.91 percentage points. Associated with this increase is the decrease in the share of households with income between $25,000 and $100,000 in high-opportunity neighborhoods. Collectively, this result is consistent with voucher households entering high-opportunity and displacing non-voucher households to relocate to other neighborhoods.

Correspondingly, the share of households with income between $50,000 and $100,000 increased in mid-opportunity neighborhoods by 0.79 percentage points. The share of households in the lower-income bin between $25,000 and $50,000 increased in low-opportunity neighborhoods by 0.96 percentage points. Although the two estimates are only weakly significant, they portray the relocation patterns of non-voucher, middle-income households opting for the next best neighborhood within their budget as a response to the influx of low-income households and increasing price tags to reside in high-opportunity neighborhoods.

It is also important to note that the share of the highest-income households with income greater than $100,000 remains stable in neighborhoods in all opportunity types. This result suggests that increasing rent prices and changing demographic characteristics had little to no impact on their residential decisions. More specifically, the incumbent high-income households in high-opportunity neighborhoods would be willing to pay a premium to stay in high-opportunity neighborhoods albeit an increasing number of low-income neighbors.

In addition, the right panel of the figure illustrates the changes in the racial compositions and portrays consistency with the income composition analysis. The share of the Black population (expected to be highly correlated with low-income levels) increased by 1.43 percentage points in high-opportunity neighborhoods, whereas it decreased in low-opportunity neighborhoods by 1.62 percentage points. This is yet again consistent with the demand shifts from voucher households from

[26] I establish similar empirical findings on changing income compositions in different neighborhoods using distributional synthetic control. I explain the procedure and present the result in Appendix B.

low- to high-opportunity neighborhoods. However, the share of the white population (expected to be highly correlated with high-income levels) decreased by 1.62 percentage points in high-opportunity neighborhoods, yet increased by 2.26 percentage points in low-opportunity neighborhoods.

5.4 Migration Analysis

5.4.1 In-Migrants to Low-Opportunity Neighborhoods

This section delves deeper into analyzing households' relocation patterns to give further support to the aggregate-level analysis above. The objective is to assess the change in migration patterns in the Dallas metropolitan area after the policy intervention by utilizing micro household-level InfoUSA data. Specifically, I examine the characteristics of migrants who are moving into low-opportunity neighborhoods in Dallas by tracking down households' residential locations over time.[27]

To assess this, I adopt a difference-in-differences that compares the characteristics of migrants moving into low-opportunity neighborhoods in Dallas to those in control metropolitan areas. 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

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

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. While utilizing the income and race measures for each household given in the InfoUSA data might seem straightforward, those measures are prone to measurement errors. This problem arises from the data provider's imputation of economic and demographic variables, which remain as a black box to the user. As a workaround, I utilize the address histories to proxy for households' characteristics similar to a strategy adopted in Asquith et al. (2023). Specifically, I use the characteristics of the neighborhoods that each household i originates from as values for Y_{it} including median household income and racial compositions of the neighborhoods.

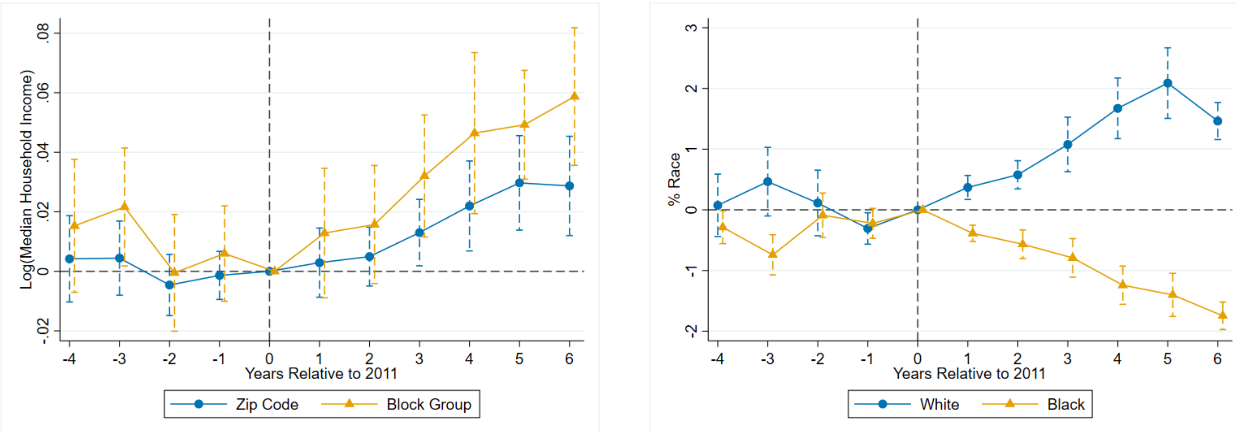
The event study estimates for household's origin median household income are presented in the

[27] I focus on the patterns of people moving into areas rather than those moving out. Most scholarly studies concur that shifts in neighborhoods are predominantly due to variations in in-migration (Asquith et al., 2023; Brummet and Reed, 2021; Ding et al., 2016; McKinnish et al., 2010).

Figure 8: 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% confidence intervals are shown in the figures. The standard errors are clustered at the zip code level.

left panel of Figure 8 where I proxy for in-migrant households' income with the ZIP codes and block groups that they originate from, depicted by blue circles and yellow triangles, respectively. There is a clear parallel trend in the pre-treatment years suggesting that the migration patterns to low-opportunity neighborhoods in Dallas did not change relative to those in the control metropolitan areas before the policy change. However, there is a clear break and a gradual change in the migration pattern sharply after the policy implementation in low-opportunity neighborhoods. By 2017, the in-migrants to low-opportunity neighborhoods originated from ZIP codes with 3% higher median household income. The effect is much stronger when I proxy households' income with the median household income of *block groups*. Households who move to low-opportunity neighborhoods tend to originate from block groups that have 6% higher median household income. The results altogether imply that households who moved to low-opportunity neighborhoods were richer than in the years before the policy change. This is consistent with the aggregate analysis shown in Section 5.3 with the share of middle-income households increasing in the low-opportunity neighborhoods.

The right panel of Figure 8 presents the results for the origin's share of white households. The result suggests that in-migrants to low-opportunity neighborhoods originate from ZIP codes with–on average–2% higher white share after the policy change as indicated by the blue circles.

Analogously, the in-migrants originate from ZIP codes with approximately 1.5% higher Black share. This, again, is consistent with the aggregate-level analysis with increasing shares of the white population in low-opportunity neighborhoods. I present analogous figures for the characteristics of in-migrants to high- and mid-opportunity neighborhoods in Appendix C.[28]

5.4.2 Relocation within High-Opportunity Neighborhoods

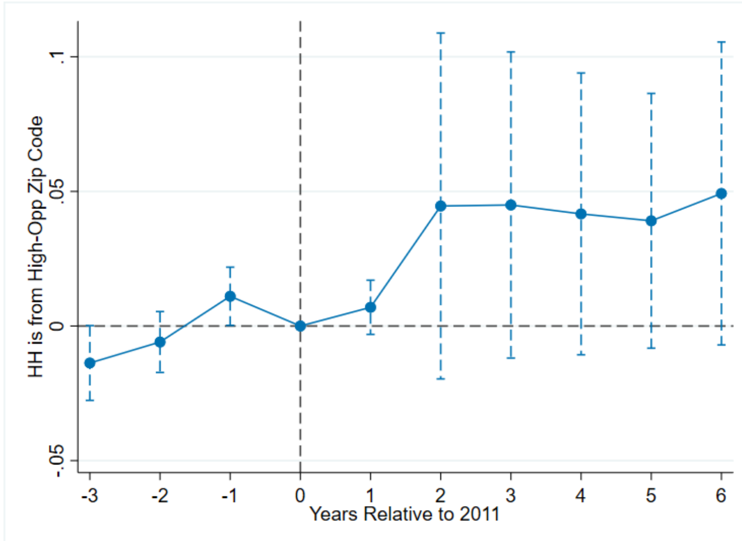
The aggregate analysis shows that the share of households earning more than $100,000 does not change in high-opportunity neighborhoods after the policy. There are two possible explanations for this: (1) high-income tenants do not respond to the policy at all and stay put in their original locations or (2) incumbent high-income households in high-opportunity neighborhoods respond by moving to different high-opportunity neighborhoods receiving relatively less voucher households. The latter involves actual moves by high-income households but will not be picked up in the aggregate analysis as they are still residing in high-opportunity neighborhoods after the move.

To interpret the zero coefficient on high-income households' moves in the aggregate analysis and distinguish which of the two aforementioned stories is lying behind the zero effect, I repeat specification (6) using an indicator for whether an in-migrant is from a high-opportunity neighborhood as the dependent variable. The results are presented in Figure 9 with weakly significant event study coefficients approximately at 0.05 after six years of policy implementation. The interpretation is that among the in-migrants to high-opportunity neighborhoods, the share of households who move from other high-opportunity neighborhoods increased by about 5 percentage points. In other words, more households are moving to high-opportunity neighborhoods from other high-opportunity neighborhoods, suggesting that there is an active internal migration among high-opportunity neighborhoods after the policy.

This empirical result gives support to the second explanation for what is happening behind the zero coefficient presented in the aggregate analysis. A possible explanation is that the influx of voucher households made high-opportunity neighborhoods less desirable to incumbent high-income households making them relocate to other high-opportunity neighborhoods that did not see a great

[28] The results analyzing in-migrants' characteristics in high- and mid-opportunity neighborhoods should, however, be taken with a grain of salt. The InfoUSA data does a wonderful job of capturing households' migration patterns over time, but it does not capture well non-white and/or poor households. Since it is the non-white and poor households who originate from low-opportunity neighborhoods and move to high- and mid-opportunity neighborhoods in response to the policy, the effects are not captured well.

Figure 9: 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.

increase in the number of voucher households. Such moves cannot be picked up in the aggregate level data as they are internal moves across high-opportunity neighborhoods.

6 A Model of Neighborhood Choice

The introduction of the 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

$$\delta_{jt}^n = \alpha_P^n \ln P_{jt} + \alpha_L^n L_{jt} + \alpha_X^n X_{jt} + \xi_{jt}^n$$

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_{jt}^n is a scalar that summarizes unobservable neighborhood characteristics. The remaining component, ε_{ijt}^n, 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 $\alpha^n = (\alpha_P^n, \alpha_L^n, \alpha_X^n)$ to be group specific.

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

$$\sigma_{jt}^n(\mathbf{P}_t, \mathbf{L}_t, \mathbf{X}_t, \xi_t^n; \alpha^n) = \frac{\exp\{\delta_{jt}^n\}}{\sum_{j'} \exp\{\delta_{j't}^n\}}$$

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_t^n 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^n_t 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

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

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

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

where $\mathcal{D}^L_{jt}(\cdot)$ 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. $\delta^n_{0t} = 0$). This normalization then implies the following relationship that can be taken directly to aggregate data for the estimation of the preference parameters:

$$\ln\left(\frac{\sigma^n_{jt}}{\sigma^n_{0t}}\right) = \alpha^n_P \ln P_{jt} + \alpha^n_L L_{jt} + \alpha^n_X X_{jt} + \xi^n_{jt} \tag{7}$$

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 (7) using repeated cross-sections from 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 char-

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

acteristics of neighborhoods and year fixed effects, λ_t^n, 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, $\tilde{\xi}_{jt}^n$. 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 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]

[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.

[31] Note that a one-time change in the number of voucher eligible units in 2011 is used as the instrument. That is, I

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

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

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 the 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.

Table 5: 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.

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 the SAFMR had on non-voucher households. The policy has made it more expensive for non-voucher households to afford a place to live in higher-opportunity neighborhoods than they could have before the policy change. To assess this, I compare the two simulated residential equilibria: one under the SAFMR and one under metro-level FMR using 2019 as the time period of interest.

Given that the model of neighborhood choice is estimated with the rent prices of the neighborhoods, I assume that renters and homeowners in a given group have the same preferences. I also assume that home prices are equal to the present discounted value of rents. Taken together, homeowners make the same location choices as renters within the same income group.

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

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

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

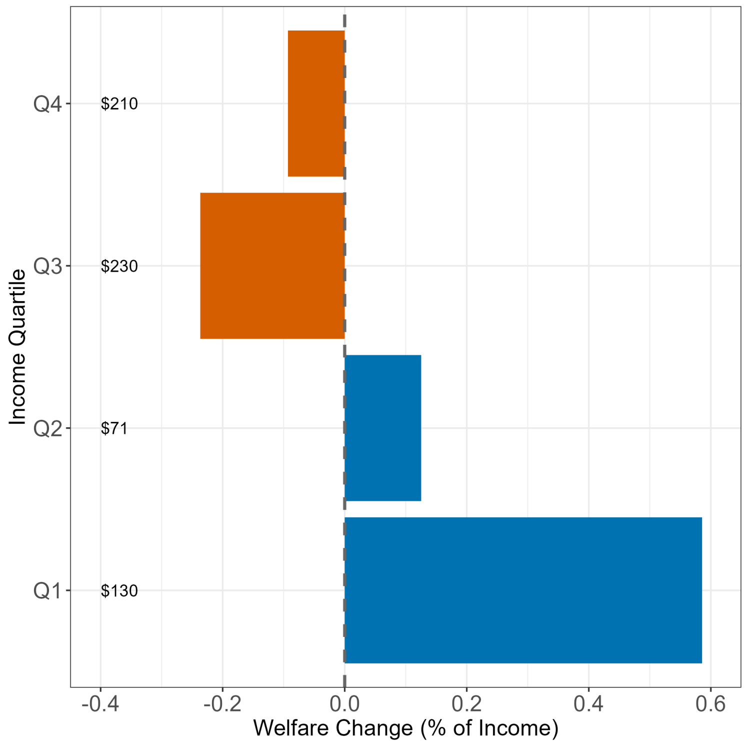
In Dallas, however, completely ignoring homeowners may be problematic in assessing welfare impacts as 58% of the total occupied housing units in 2019 were owner-occupied as shown in Table 2. To account for this aspect, I assume that all homeowners receive a flow of rental income from their housing portfolio. Thus, the total welfare effects of income group n are defined as the sum below

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

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.[35]

[35] 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.

Figure 10: 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.

7.1 Welfare Impact from Small Area Fair Market Rents

As the main welfare analysis, I compute the average change in each group's welfare resulting from the introduction of SAFMR. This analysis requires that I simulate an equilibrium under MFMR, drawing on the model's parameters estimated in the previous section. However, this is a slightly complicated process as I do not explicitly model residential decisions made by the *voucher* households. I refrain from modeling voucher households' location choices as their optimization problem is a much more complex one faced with various constraints and discriminatory frictions.[36] The aggregate data from the PoSH constrains a detailed modeling of this complex decision process.

Since I cannot allow voucher households to self-sort through the model, I need to take a stance on how the voucher households would have been located in 2019 had there been no introduction

[36] 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., 2019).

of SAFMR in 2011 to simulate an equilibrium under MFMR in 2019. To simplify this issue, I assume that the spatial distribution of voucher households in Dallas remains the same in 2019 as it was in 2010. That is, I fix the proportion of voucher households living in each neighborhood by force-locating them in a pattern resembling that of 2010. The rationale behind this is to simulate an equilibrium where the 2019 voucher households face similar constraints as they did prior to the introduction of SAFMR. While this simplification has obvious caveats and limitations as I am not allowing them to freely choose locations by themselves, it provides a plausible snapshot of their probable spatial distribution in a scenario without SAFMR.

I compare the simulated equilibrium under this assumption to the actual equilibrium realized in 2019 and report the welfare consequences of the SAFMR in Figure 10.[37] It is immediately clear from the estimates that the welfare for high-income households in the third and fourth income quartiles was hurt due to the policy implementation. More specifically, they lost \$230 and \$210 in annual rents which account for about 0.2% and 0.1% of their annual income, respectively. On the other hand, lower-income households in the first and second income quartiles gained welfare due to lower rent prices in lower-opportunity neighborhoods. In fact, the non-voucher households in the first income-quartile group experienced a substantial welfare gain that accounts for 0.6% of their income.

Overall, the SAFMR seemed to have had a marginally negative welfare impact on high-income non-voucher households, whereas it led to a substantial welfare gain for non-voucher households in the first income-quartile group. This policy shift from MFMR to SAFMR not only helped the direct beneficiaries (i.e. the voucher households) to gain access to higher-opportunity neighborhoods but also indirectly benefited the low-income non-voucher households to live in housing units in low-opportunity neighborhoods at a more affordable rates.

7.2 Welfare Impact from Housing Choice Voucher Program

In the previous section, I demonstrated how the implementation of the SAFMR to the traditional metro-level design of the payment standards impacts households' welfare. However, it is equally important to consider the welfare impact of the HCVP itself. To estimate this, I simulate two sets

[37] For correct comparison with the simulated counterfactual equilibrium, I also simulate a baseline equilibrium using the actual data for exogenous neighborhood characteristics and estimated fixed effects. I discuss how well my model fits the data in Appendix B.

of equilibria using the estimated model. First, I take away the voucher program from the world with MFMR by allowing the voucher households to self-sort in the model using the preferences of the first income-quartile group.[38] By comparing the simulated equilibrium with no HCVP in place to the one with the metro-level FMR in place, I am able to calculate the welfare impact of implementing the metro-wide payment cap to determine rental units' eligibility for voucher households. The other simulation comes from removing the voucher program from the world with SAFMR.[39] This allows me to capture the welfare impact of instituting the voucher program with a more flexible version of the payment caps.

Figure 11 presents the welfare impacts for both scenarios. The left panel illustrates the welfare impacts when MFMR is superimposed on an environment without the voucher program. Except for those in the highest-income quartile, most non-voucher groups experience welfare losses. Notably, the welfare loss for the first income quartile is substantial, amounting to 2.92% of their annual income. The right panel, on the other hand, showcases the welfare consequences of implementing SAFMR to a world without the voucher program. The welfare impact for the second to fourth income quartiles is consistent with the institution of MFMR, but the first income quartile's negative welfare impact almost halves, accounting for 1.52% of their annual income.

The substantial welfare loss concentrated in the lowest-income group in both of the scenarios likely stems from the HCVP's effect: it concentrates voucher households' demand for housing in low-opportunity neighborhoods.[40] This demand concentration inevitably pushes up rent prices in those areas, making it difficult for non-voucher residents living there to find housing at more affordable rates. However, the SAFMR diverts some of voucher households' demand for housing to higher-opportunity neighborhoods, thereby reducing the welfare loss for the lowest-income group in comparison to the MFMR approach.

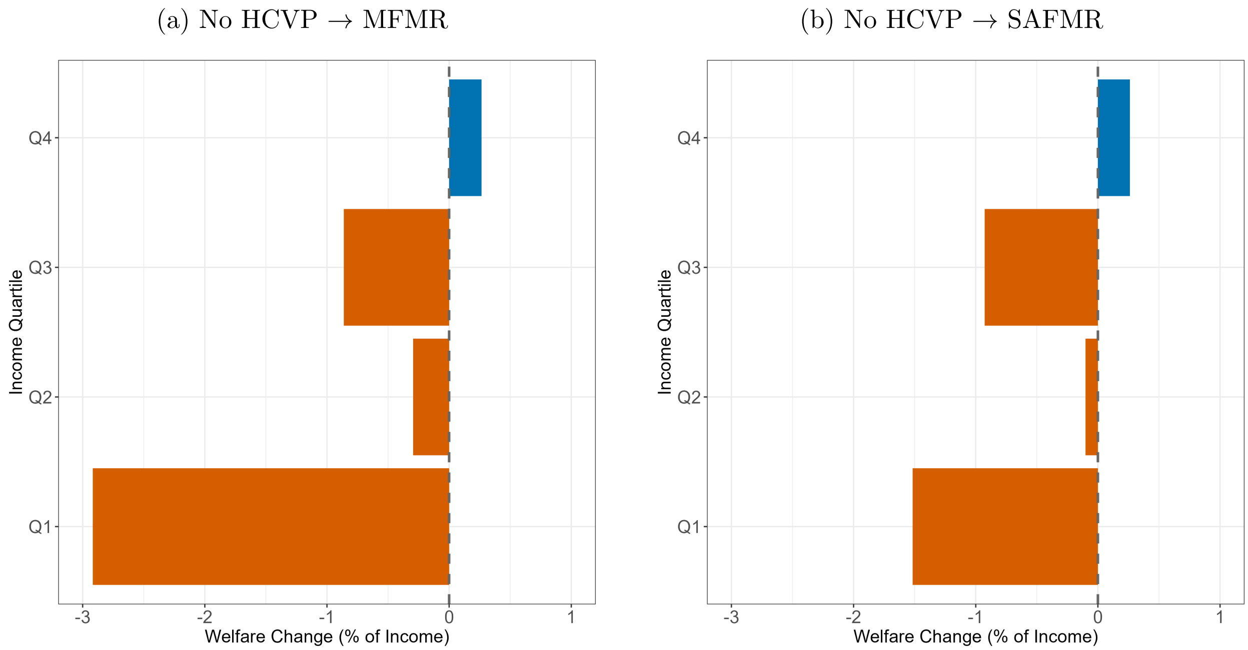
The welfare results presented here combined with the ones in the previous section prove that there are two competing effects associated with the HCVP. On one hand, the voucher program itself damages the welfare of the very group that this program is designed to help. Although the voucher program allows a small fraction of low-income households to gain access to better-opportunity

[38]This simulation is based on the year 2010 when the SAFMR was not in place.

[39]This simulation is based on the year 2019 when the SAFMR was in place for 8 years in Dallas.

[40]This result is consistent with Susin (2002) which finds that low-income non-voucher households experienced a faster increase in their market-rate rent prices in metropolitan areas with more abundant vouchers.

Figure 11: Welfare Impacts of HCVP



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.

neighborhoods, it comes at the welfare cost of the low-income households who are not the direct beneficiaries of the program. If a policymaker values the potential positive impact on the voucher households and decides to implement the program, then the small area version of the FMR allows the welfare cost to be distributed more evenly across the income distribution compared to the metro version.[41]

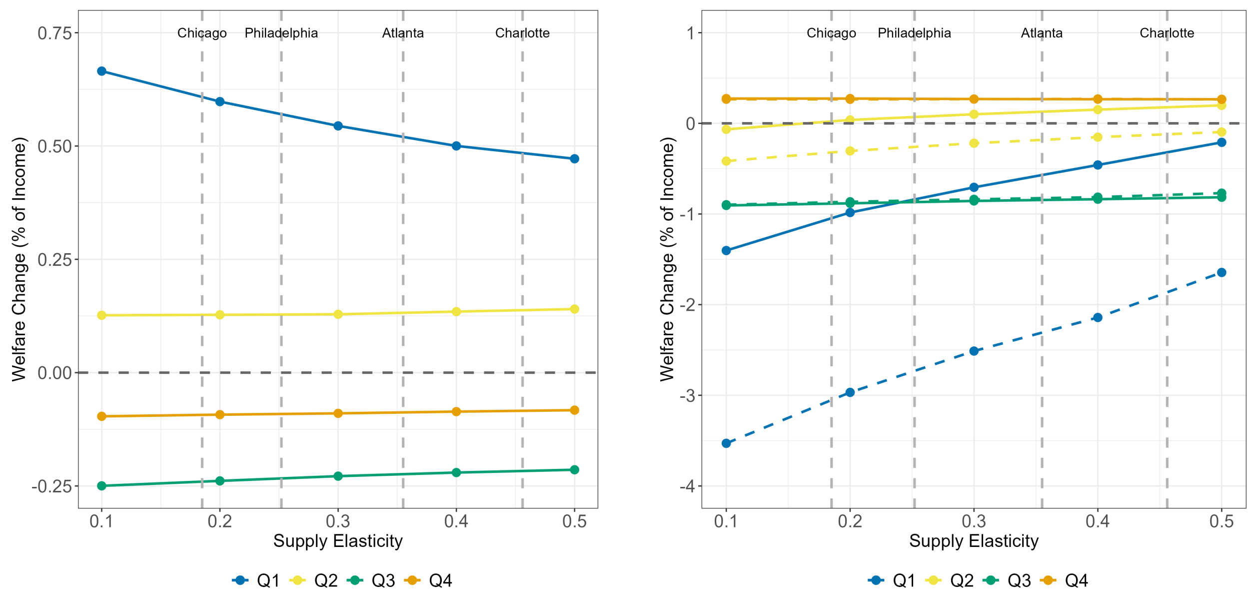
7.3 Welfare Impact under Alternative Housing Supply Elasticities

The SAFMR, as previously discussed, was extended to multiple metropolitan areas in 2018, making it important to take a step further from Dallas and consider the potential welfare implications in these other metros. One key dimension where these areas differ is their housing supply elasticities. For example, the SAFMR was mandated in both Chicago and Charlotte with the elasticity values from Baum-Snow and Han (2023) of 0.185 and 0.456, respectively. Thus, it is important to assess

[41]Directly comparing the benefits/losses accrued by the voucher and non-voucher households is out of the scope of this paper. The limitation comes from my inability to explicitly model voucher households' residential decisions to capture the benefits that these people get from the policy.

Figure 12: Welfare Impacts under Alternative Housing Supply Elasticities

(a) MFMR → SAFMR (b) No HCVP → MFMR/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 (2023).

the welfare impact of various designs of voucher programs by simulating multiple equilibria under alternative supply elasticities (i.e. vary ψ in housing supply calibration).

One would expect that higher supply elasticity reduces the equilibrium effects leading to lower welfare consequences across all income groups. For example, if it is easier to build more homes in high-opportunity neighborhoods, the magnitude of the price increase due to SAFMR will be smaller as more supply generally reduces prices, and vice versa in low-opportunity neighborhoods. The welfare loss associated with the high-income non-voucher households will then be smaller as the price increase they face will be lower.

The welfare impact of going from MFMR to SAFMR is shown in the left panel of Figure 12 where I plot the welfare impact in shares of each group's annual income for different supply elasticities in the x-axis. Given that the welfare impact on non-voucher households in the second through fourth income-quartile groups is not significant, to begin with, supply elasticity plays little to no role in affecting the magnitude of the welfare impact. However, the welfare implication for the first income-quartile group was in line with the expectation. The welfare gain for them is the highest when the supply elasticity is the lowest because the reduction in the rent prices due to the SAFMR will be the greatest when it is more difficult for the supply to respond to the demand. The amount of gain reduces as supply becomes more elastic.

The right panel of Figure 12 shows the welfare impact of implementing the voucher program in the world without one. The dashed lines represent the impact coming from the implementation of MFRM for each income group, whereas the solid lines depict that from instituting SAFMR. Analogous to the previous result, supply elasticity plays little role in the welfare of non-voucher households in the second to fourth income-quartile groups. Again, however, it has a substantial impact on the welfare of the lowest-income non-voucher households. The negative welfare associated with the implementation of the voucher program itself becomes smaller in magnitude as supply elasticity increases.

In summary, these findings underscore that supply elasticity most profoundly influences the welfare of the lowest-income non-voucher households. Policymakers should carefully consider the housing supply elasticity of an area when implementing the voucher policy. Whether re-designing existing voucher subsidies or launching a program itself, such considerations are paramount since they directly impact the demographic group this voucher program is primarily designed to assist.

8 Conclusion

This paper examines the equilibrium effects of the SAFMR, the new design of the largest federally run housing subsidy program in the U.S. This redesign increased the generosity of the housing subsidy for voucher households to live in high-rent, high-opportunity neighborhoods. I employ a simple difference-in-differences framework to assess the changes in the equilibrium of rent prices and the income and racial distributions of households across neighborhoods in Dallas, the very first metropolitan area to adopt this redesigned voucher subsidy. Then, I adopt a structural model of neighborhood choice to assess the welfare impact this new equilibrium has on non-voucher households. Using the estimated model, I also quantify the welfare impact of the HCVP.

The empirical findings highlight that the SAFMR has led to changes in the spatial distribution of households and rent prices in the area. While the policy was designed to increase low-income voucher households' access to high-opportunity neighborhoods, it has had broader equilibrium effects on rent prices and segregation patterns due to the re-sorting of both voucher and non-voucher households. On one hand, it successfully relocated some voucher households out of high-poverty areas to high-opportunity neighborhoods, contributing to a more egalitarian residential equilibrium in terms of income and racial mix. On the other hand, it caused a more polarized rent equilibrium, making expensive neighborhoods even more costly and affordable neighborhoods even cheaper.

With the estimated structural model, I find that the SAFMR had contrasting welfare impacts on high- and low-income non-voucher households. The rent price appreciation in high-opportunity neighborhoods resulted in a marginal welfare loss for the high-income non-voucher households. Conversely, the overall price decrease in low-opportunity neighborhoods led to a sizable positive welfare gain for low-income non-voucher households. However, the implementation of the HCVP itself, irrespective of the design of the payment standard, led to a significant welfare loss for low-income non-voucher households. This loss was due to an increase in demand in low-opportunity neighborhoods from voucher households. The model also suggests that a higher housing supply elasticity in a metropolitan area reduces the magnitudes of these welfare impacts.

By increasing low-income voucher households' access to higher opportunities, the Housing Choice Voucher Program, along with its redesigned Small Area Fair Market Rents, 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. My paper emphasizes the need for a more holistic and comprehensive approach when designing and implementing housing policies. It underscores the importance of striking the right balance between providing affordable housing for low-income households, ensuring socioeconomic and demographic integration, and optimizing overall welfare.

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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.3 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-

[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.

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.4 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 recently. I document this in Figure C.5 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.6. 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 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 5.2.2, 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.7 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 last figure suggests that low-opportunity neighborhoods did not seem to have experienced much change in the income composition.

B.4 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.5 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.6 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 $\mathbf{P}$ and $\mathbf{L}$ in 2019 given the exogenous neighborhood characteristics $\mathbf{X}$ 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.10. 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

$$\hat{\delta}_{jt}^{n} = \hat{\alpha}_{P}^{n} \ln P_{jt} + \hat{\alpha}_{L}^{n} L_{jt} + \hat{\alpha}_{X}^{n} X_{jt} + \hat{\lambda}_{j}^{n} + \hat{\lambda}_{t}^{n} + \hat{\hat{\xi}}_{jt}^{n}$$

and plot them against the observed shares in the data in Figure C.11. 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.

C Appendix: Figures and Tables

Table C.1: 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 Chetty et al. (2018).

Table C.2: 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.

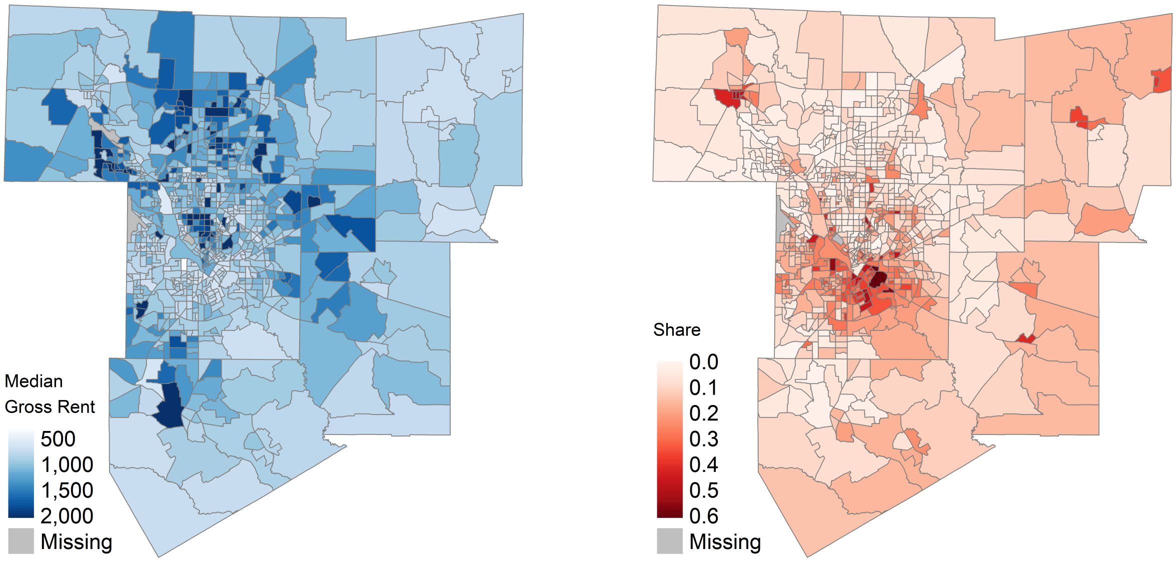
Table C.3: Estimates of Neighborhood Preference Parameters for Non-Voucher Households (OLS)

	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.

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

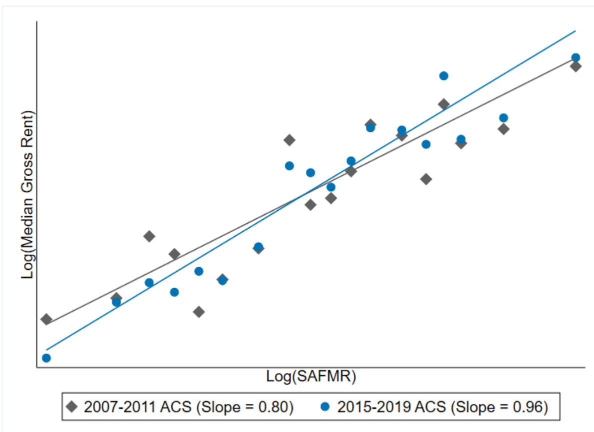
(a) Median Gross Rent (b) Below Poverty



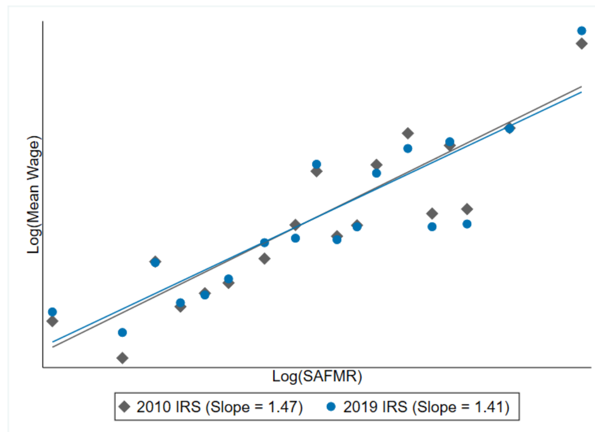
Notes: The figures above show maps of Census tracts in Dallas based on the 2010 geographical designation. The left panel is a map of Census tracts in the Dallas-Plano-Irving, TX Metro Division with their respective median contract rents plotted. The right panel is based on the share of households living 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.2: Long-Run Equilibrium - Empirical Version

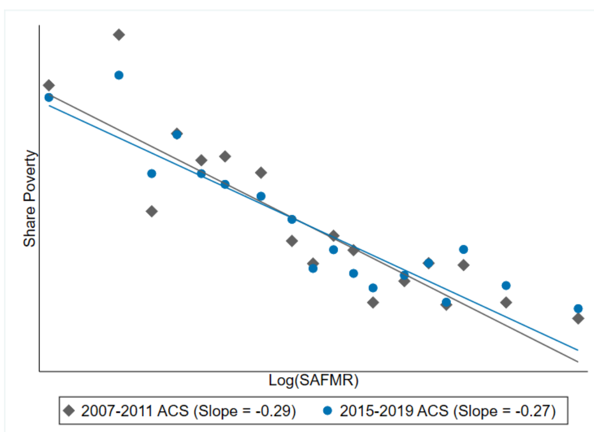
(a) Rent Price Gradients



(b) Wage Gradients



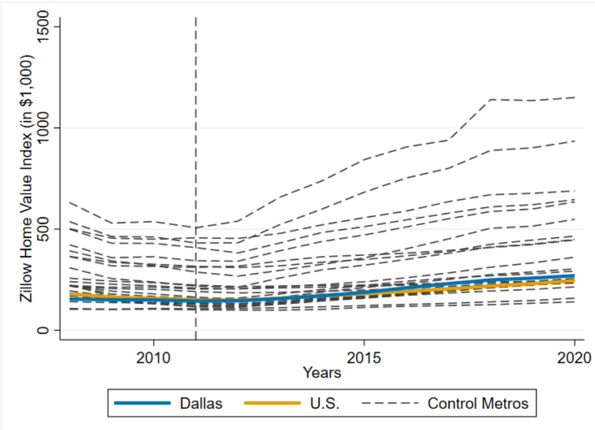
(c) Share Poverty Gradients



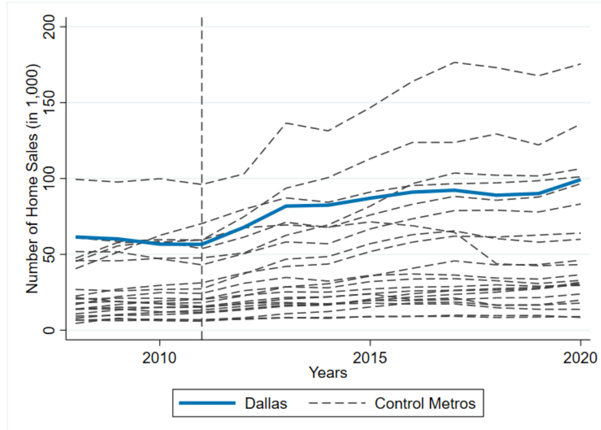
Notes: The figures above show the empirical version of the long-run gradients of each respective outcome variable. The gray lines represent the initial equilibrium before the policy change, whereas the blue lines represent the policy-induced equilibrium. All variables are demeaned for each year to make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

Figure C.3: Trends in Housing Market in Select Metropolitan Areas and U.S. (2008-2020)

(a) Housing Price



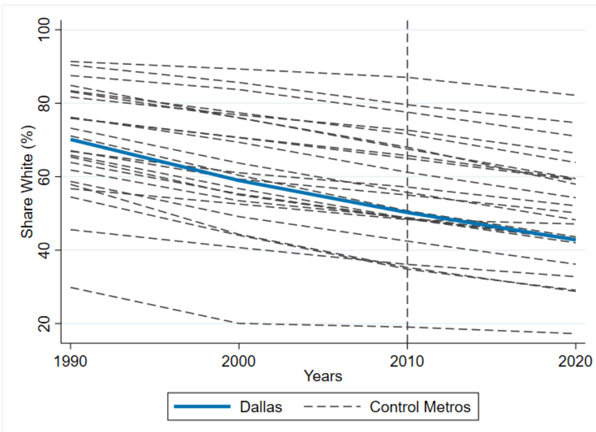
(b) Number of Home Sales



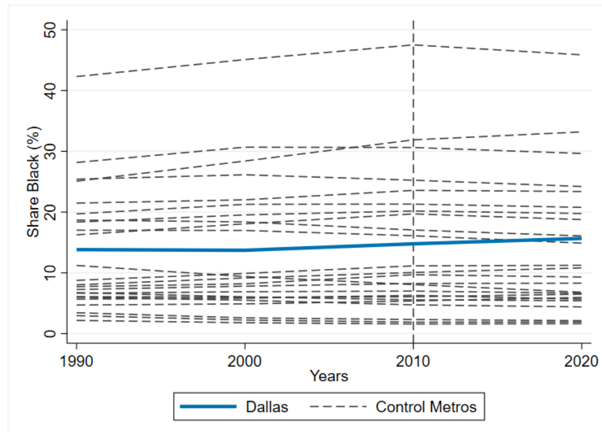
Notes: The figures above plot the trends in the housing market for both the Dallas metro and other select control metropolitan areas. The left panel plots the trend in housing prices as measured by Zillow's Home Value Index, and the right panel plots the trend in the number of home sales from Zillow's 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.4: Trends in Racial Compositions in Select Metropolitan Areas and U.S. (1990-2020)

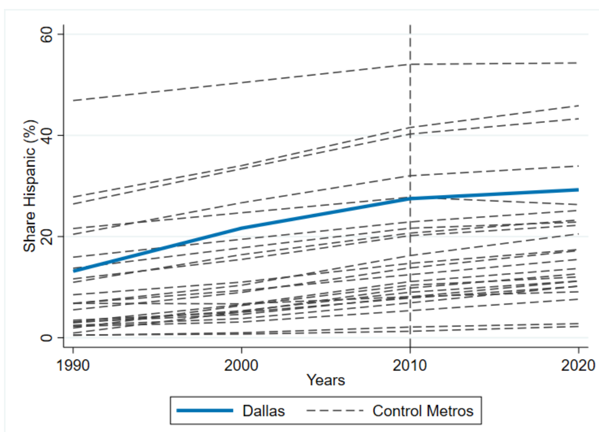
(a) Share White



(b) Share Black



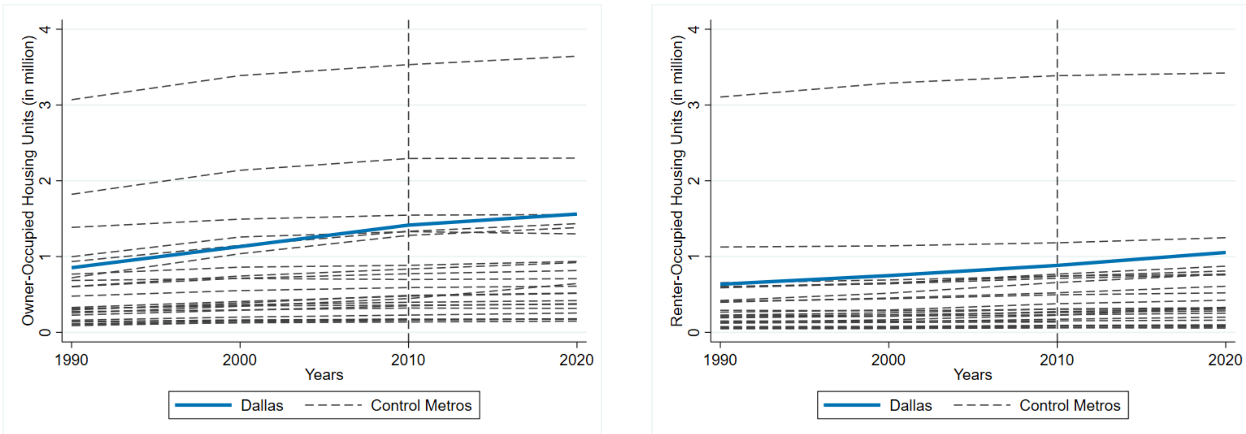
(c) Share Hispanic



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

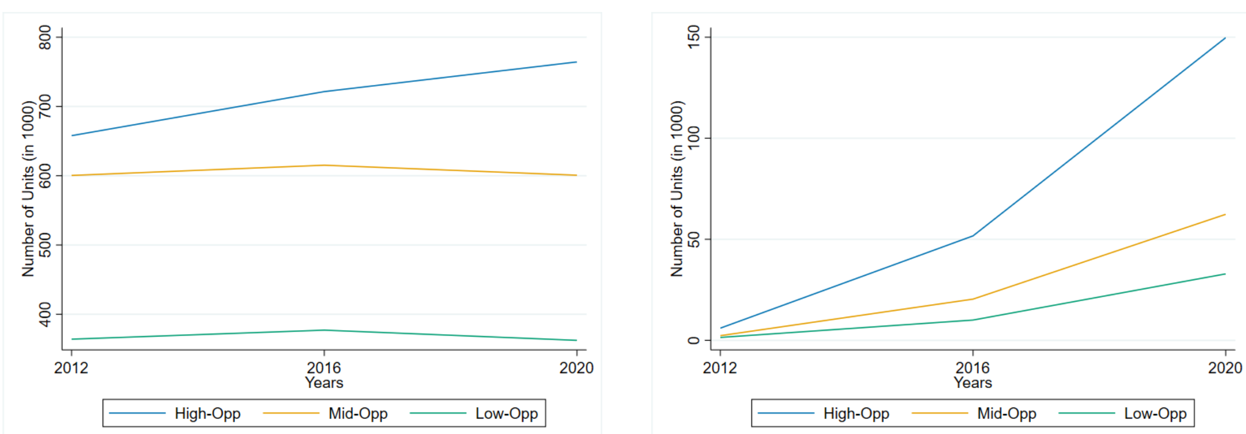
(a) Owner-Occupied Units (b) Renter-Occupied Units



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.6: Trends in Housing Supply in Dallas

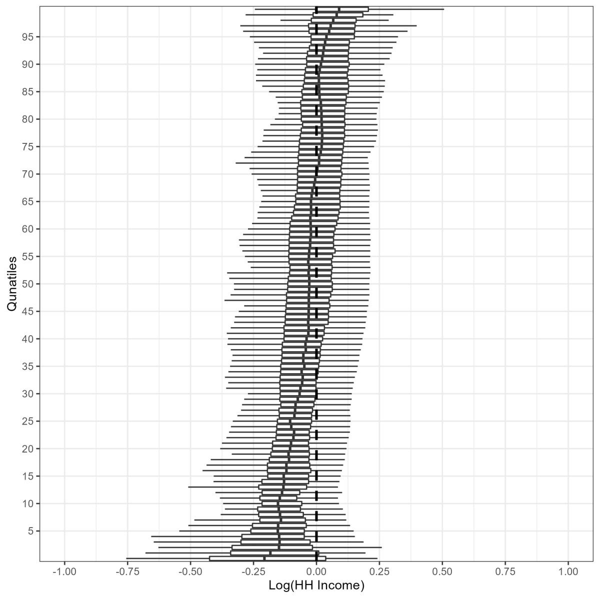
(a) Total Housing Units (b) Number of New Constructions (Built Post-2010)



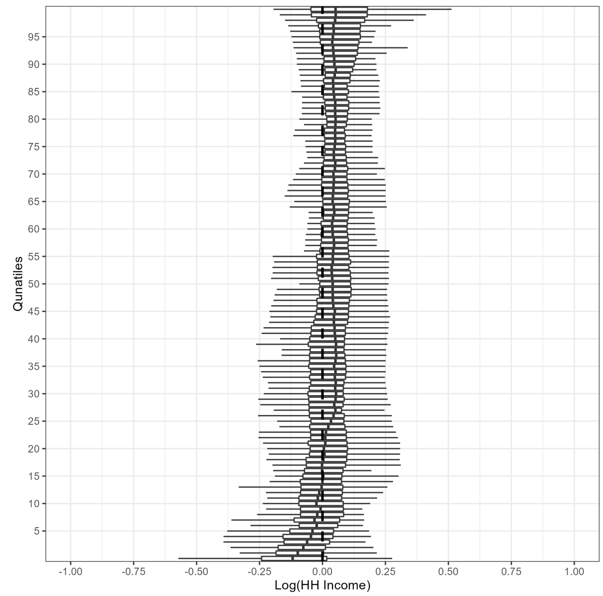
Notes: The figures above plot the number of total housing units (left panel) and new constructions as defined by those that are built after 2010 (right panel) in the Dallas metro by neighborhood opportunity types over the specified time period. The years 2012, 2016, and 2020 represent the 2008-2012,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

Figure C.7: Household Income–Distributional Synthetic Control

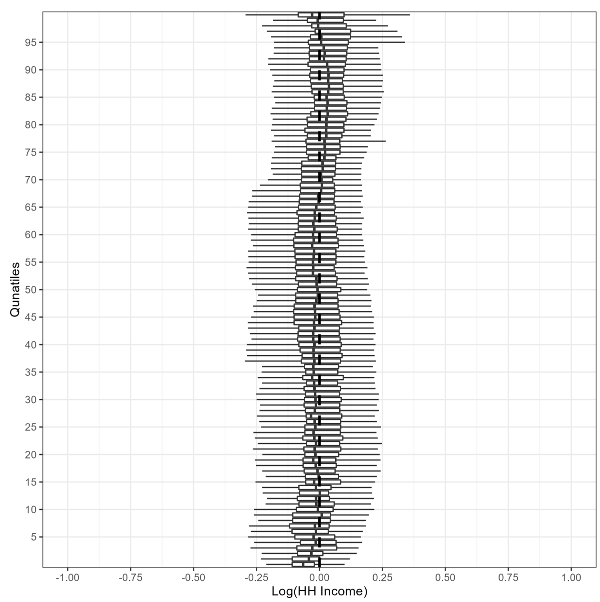
(a) High-Opportunity Neighborhoods



(b) Mid-Opportunity Neighborhoods



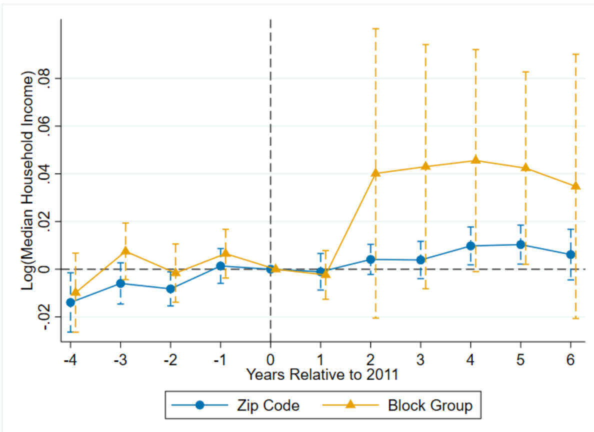
(c) Low-Opportunity Neighborhoods



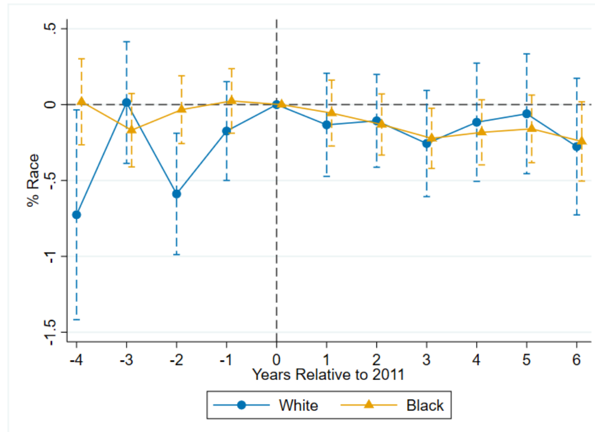
Notes: The figures above depict whisker plots of the neighborhood-level treatment effects from the distributional synthetic control averaged across post-treatment years from 2012 to 2017 for each quantile. The distributional synthetic control has been performed for each ZIP code based on its opportunity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

Figure C.8: Characteristics of In-Migrants to High-Opportunity Neighborhoods

(a) Origin Neighborhood's Median HH Income



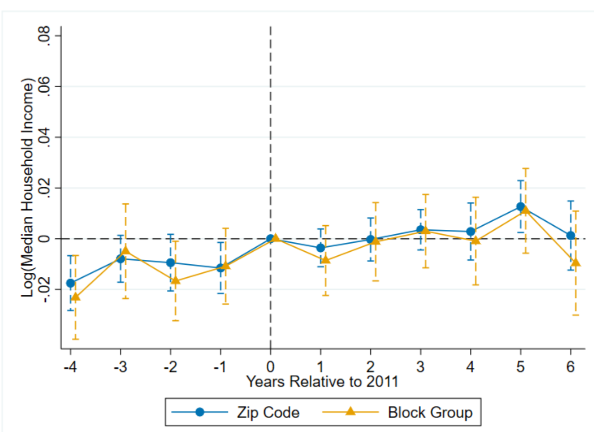
(b) Origin Neighborhood's Racial Composition



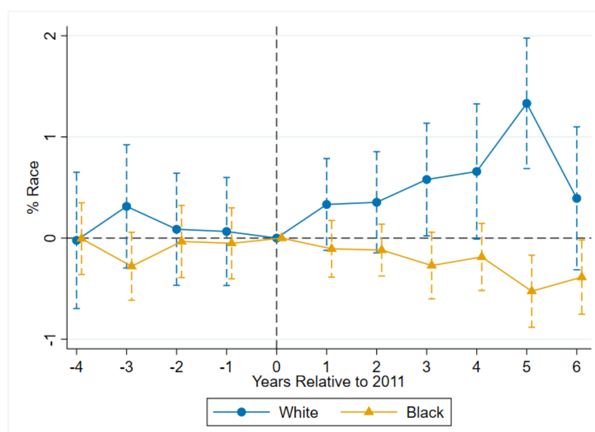
Notes: The figures above plot the event-study coefficients of the effect of SAFMR on in-migration patterns to high-opportunity neighborhoods. In the left panel, the dependent variable is the log median household income of a neighborhood (either zip code or block group) an in-migrant originated from. 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.9: Characteristics of In-Migrants to Mid-Opportunity Neighborhoods

(a) Origin Neighborhood's Median HH Income

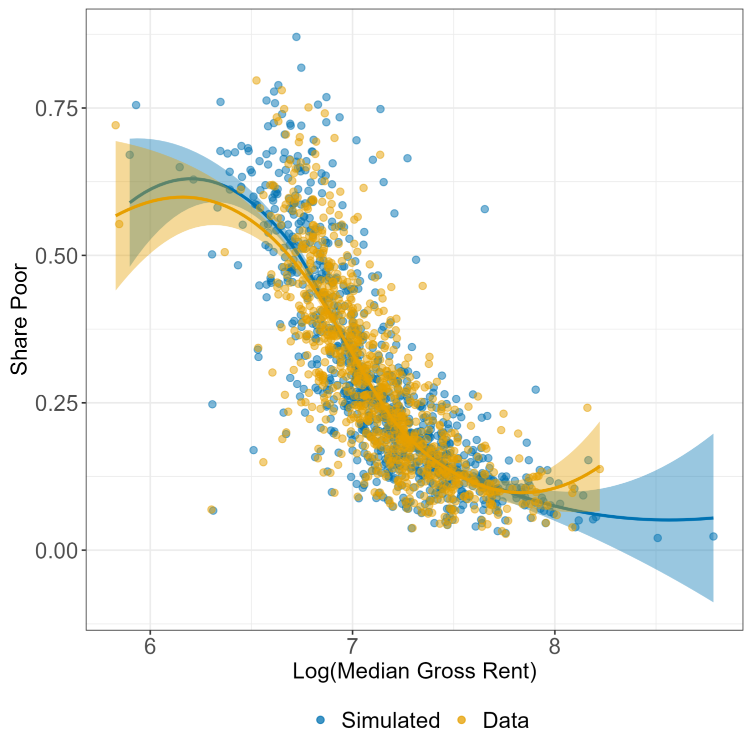


(b) Origin Neighborhood's Racial Composition



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.

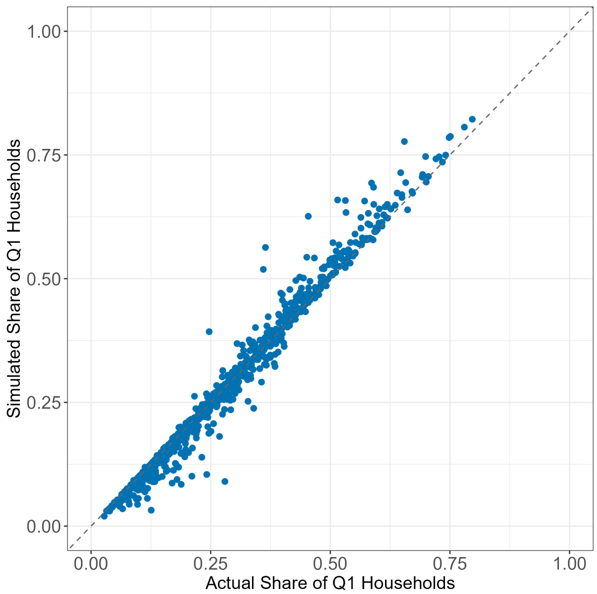
Figure C.10: Model Fit - Actual v. Simulated Equilibria



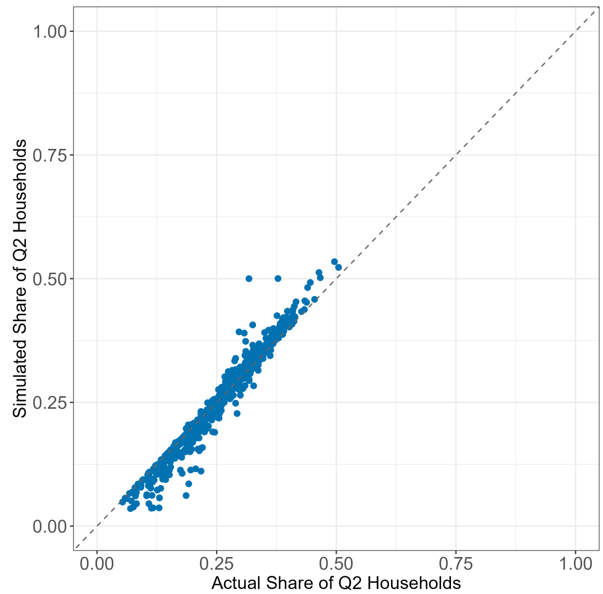
Notes: The figure plots the joint distribution of rent prices and shares of poor households in neighborhoods in Dallas. Yellow dots represent the distribution given in the 2015-2019 ACS data, whereas blue dots represent those that are simulated using the estimated model. Local polynomial regression fits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

Figure C.11: Model Predicted v. Actual Shares of Households in Income Groups

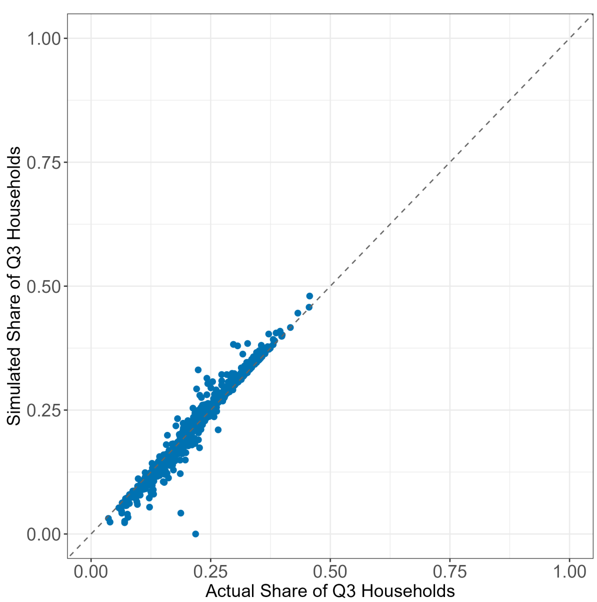
(a) Q1 Households



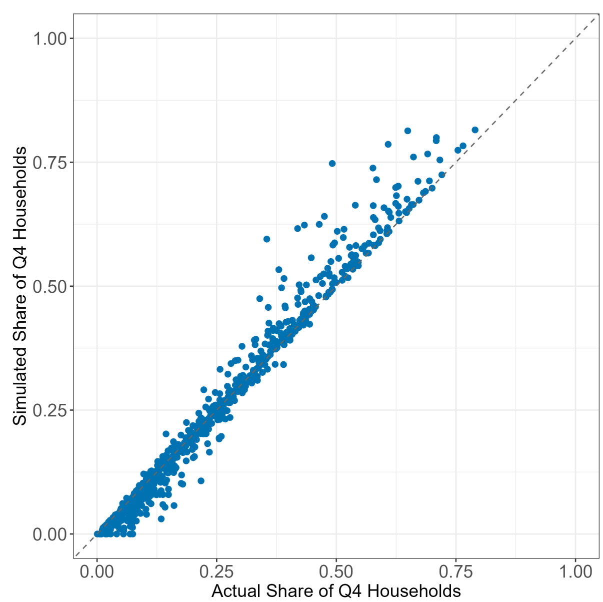
(b) Q2 Households



(c) Q3 Households



(d) Q4 Households



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.