Single-Family Rentals and Neighborhood Racial Integration*

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Abstract

Neighborhood racial segregation continues to be a major social problem within America's metropolitan areas. One factor possibly accounting for segregation is the inability of minority households to afford housing in White neighborhoods, where housing units historically have been largely owner-occupied single-family homes. In recent years there has been a dramatic shift in the housing makeup of many of these neighborhoods, with single-family rentals increasing in share. Rentals lower the cost of neighborhood entry. Our results, which suggest that these rentals reduce neighborhood racial segregation for Blacks, support policies that seek to maintain and grow single-family rentals within White neighborhoods.

Keywords: racial segregation, single-family rental housing, housing affordability

JEL Classification: J15, J68, R21, R23, R31

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1. Introduction

Neighborhood racial segregation continues to be a major social problem within America's metropolitan areas. Segregation has been linked to a whole host of inequalities, including access to jobs (Weinberg, 2000), schooling and single parenthood (Cutler and Glaeser, 1997), and future earnings (Chetty and Hendren, 2018; Chetty et al., 2014). One possible factor accounting for segregation is that housing in White neighborhoods tends to be relatively expensive, owner-occupied, single-family homes that many minority households, because of their lower incomes, may find unaffordable. Either these households cannot afford the price of these homes, or they are unable to satisfy mortgage underwriting criteria.

Since the Great Recession, many White neighborhoods have changed in a way that has made single-family (SF) housing more affordable within these neighborhoods. Namely, SF *rental* units are now a larger share of the total number of SF homes and a larger share of the total number of all housing units. The growth in SF rentals has come from the conversion of SF owner-occupied homes and increasingly from new construction. By allowing minorities to avoid the transaction costs and down payment requirements associated with homeownership, rentals lower the cost of neighborhood entry and increase the affordability of housing. The question we address in this paper is whether the switch in SF housing tenure in favor of rentals has increased racial integration within urban neighborhoods where minorities have historically been underrepresented. The importance of addressing this question is twofold. First, moving forward, SF rentals are expected to remain an important part of the housing inventory and therefore may bring permanent declines in the level of neighborhood segregation. Second, whether more affordable housing of *any kind* within White neighborhoods will decrease housing segregation is unresolved within the empirical literature, with roughly equal numbers of studies suggesting opposite answers to the question. From a policy perspective, reliable evidence on this issue is therefore imperative, as policymakers seek the best way to better racially integrate America's neighborhoods.

Our analysis is based on a balanced six-year panel of thousands of neighborhoods (census block groups) falling within nine of the ten largest urban counties within the state of Florida. For the years 2008 through 2013, we relate shifts in a neighborhood's housing stock in the current year in favor of SF rentals to changes in the U.S. Census Bureau's estimated average racial composition within the neighborhood measured over the current and future four years. Hence, the estimation allows changes in the neighborhood's share of SF rentals to have a long-run effect on the percentage of the neighborhood's residents who are minorities, where the latter are broken down into non-Hispanic Blacks (henceforth, Blacks) and Hispanics. Because these percentages can rise in response to SF rentals either because of minority entry or non-Hispanic White (henceforth, Whites) exit, we also estimate models that reveal the underlying migratory patterns across racial groups that account for our neighborhood compositional results. Models are also estimated that relate changes in the share of SF rentals to changes in the presence of each racial group by housing tenure (renters versus homeowners) measured as a percentage of the neighborhood's households.

Results obtained from the estimation of our neighborhood compositional models show that within neighborhoods where Blacks have historically been underrepresented, an increase in the share of housing units represented by SF rentals increases the share of the neighborhood's residents who are Black, resulting in greater racial integration. The effect is both highly statistically significant and nontrivial in magnitude. Of particular importance is that the effect can be found regardless of neighborhood income level and whether the dominant racial group within the neighborhood is Whites or Hispanics. The housing tenure models indicate that the increase in Black share comes from renters and not homeowners. Also of considerable importance is that the results from the estimation of our migration models show that the increase in integration is due mostly from Black entry and not the exit of Whites or Hispanics. The results from replicating our analysis for Hispanics as the minority group contrast to the results obtained for Blacks. An increase in the share of SF rentals has varying effects on the share of Hispanic residents across our different neighborhood types, but generally, these effects are either not statistically significant or negative in sign.

In the next section (2), documentation is provided on the increase in SF rentals. Studies that have some relevance to our inquiry are reviewed in Section 3. A conceptual framework underlying our empirical methodology is provided in Section 4. Section 5 describes our panel of Florida neighborhoods. The three sets of models we estimate (racial composition, housing tenure, and migration) are described in Section 6. Sections 7, 8, and 9 contain our results from estimating each model set, respectively. Results from checks on the robustness of our results are provided in Section 10. Our conclusions are presented in Section 11.

2. The Growth in Single-Family Rentals

We document the growth in SF rentals using data from the American Community Survey (ACS) and from the Florida county property tax rolls. Figures 1 and 2, which are based on our calculations using the ACS, show the upward climb in the total number of SF rentals and as a percentage of the SF housing stock from 2005 to 2017 for the nation and the state of Florida, respectively.[1] At the national level, the rental percentage climbed roughly 4 percentage points, from 13 to 17 percent. Particularly strong was Florida's growth in rentals, with an increase of 7 percentage points, from 13 to 20 percent.

[1] The figures also show that at the national level, SF rentals as a percentage of all SF homes peaked in 2014 and declined somewhat from 2014 to 2017, while in Florida the percentage leveled off after 2015.

[Figures 1 and 2 about here]

The property tax roll data come from the Florida Department of Revenue. Each Florida county is required to submit its property tax roll annually to the Department of Revenue. Due to the voluminous nature of these data (they contain millions of records covering every property in the state for the years 1995 to 2018), we choose to work with the largest ten counties in estimating our models. One set of county tax rolls, those from Hillsborough County, was missing geographical identifiers that prevented us from placing properties in the correct neighborhood. Our resulting sample of nine counties contains 47.3 percent and 48.9 percent of all single-family housing units in the state for the years 2008 and 2013, respectively, which are the beginning and final years of our panel. As we detail later in the paper, the rolls provide a way to reliably estimate the number of SF rentals. Of all of the SF rentals in the state, 40.2 percent and 42.2 percent are found within our nine counties at the beginning and end of our panel.

As shown in Figure 3, our sample includes neighborhoods (numbering in the thousands) from all six regions within the state.[2] Table 1 shows for all counties combined and for each of the nine counties separately the total number of SF rentals, their share of the SF housing stock, and their share of all housing units for the years 2008, 2013, and 2018.[3] All nine counties experienced dramatic increases in the number of SF rentals over the ten-year period. Together, the number of SF rentals grew from 350,071 in 2008 to 504,329 in 2018—an increase of 44 percent. Regarding SF rentals as shares of the SF housing stock and of the total number of housing units, there are positive changes between 2008 and 2013 for all counties and generally a leveling off after 2013. The shares of the total number of SF units for all counties combined are 15.9, 20.2, and 20.0 for

[2] The regions of our nine counties are north (Duval), central west (Pinellas and Polk), central east (Orange and Brevard), southwest (Lee), and southeast (Miami-Dade, Broward, and Palm Beach).
[3] Total housing units is the sum of single-family homes plus the number of condominiums and individual apartments.

2008, 2013, and 2018, respectively. The shares of the total number of housing units are 8.2 (2008), 11.0 (2013), and 10.8 (2018).

[Figure 3 and Table 1 about here]

Additional documentation on the growth in SF rentals has been provided by Freddie Mac (FM, 2019). FM assesses the importance of SF rentals within the national rental housing market. Based on its analysis of ACS data, FM concludes that SF rentals are now the largest segment of the rental market by valuation and households served and that since the Great Recession, they have been the fastest-growing segment of renter-occupied households. A key contributor to this growth that is likely to increase in importance is that SF rentals are now a new asset class for institutional investors (Eisfeldt and Demers, 2015; Ganduri et al., 2019; Mills et al., 2019).[4]

Another fact of interest is the source of the SF rentals. FM reports that among single-family homes, 4.9 percent are now being built as rentals, significantly higher than the 2.2 percent share averaged in the 1980s and 1990s. Hence, while SF rentals come largely from the conversion of previously existing owner-occupied homes, a growing number are also from new construction. We conducted our own analysis of the sources of the SF rentals in our Florida counties by using the property tax rolls to study the history of individual properties. This involved using the unique number identifying the parcel to find it on previous tax rolls. In any one year, roughly 90 percent of new SF rentals are found to come from conversions and the rest from new construction.

We constructed from the tax rolls one additional table that serves to motivate our analysis of the effects of SF rentals on neighborhood racial integration. First, we computed the percentages of Blacks and Hispanics at the county level for 2008, the first year of our panel. Then for each county, we identified those neighborhoods where the Black (Hispanic) percentage of the neighborhood in

[4] Ganduri et al. (2019) report that institutional investors have increased their holdings of single-family homes 30-fold between 2010 and 2016. Mills et al. (2019) provide evidence on the various factors underlying these increased holdings.

2008 was less than the county Black (Hispanic) percentage. Panels A and B of Table 2 show changes from 2008 to 2018 in the housing stocks within neighborhoods where Blacks and Hispanics are underrepresented, respectively.[5] It is within these neighborhoods where SF rentals may have allowed a reduction in residential neighborhood segregation. Shown in the table are the number of housing units, the number of single-family rentals, and the number of housing units other than SF homes. The latter consist largely of the number of units found within multifamily properties, both apartments and condominiums. They are listed in the table because these units, along with single-family rentals, are the housing shares included in our estimated models, with the share of SF owner-occupied housing serving as the reference category. Also shown in Table 2 are SF rentals as shares of all SF homes and of all housing units, as well as other housing units as a share of all housing units.

[Table 2 about here]

Note first that the total number of housing units and the number of SF rentals grew in both Black and Hispanic underrepresented neighborhoods from 2008 to 2018. The growth in SF rentals was especially remarkable, 47 percent in both types of neighborhoods. In contrast, the growth in the number of other housing units was flat over the period. Rows for the individual counties display the same contrast between the strong growth of SF rentals relative to the growth of other housing units. As a result of these divergent growth patterns, within neighborhoods where Blacks are underrepresented, SF rentals grew as a percentage of all housing units, from 7 to 10 percent, while other housing units declined in share from 50 to 46 percent. Similar changes were registered for

[5] Our panel ends in 2013 but employs the ACS 5-year average to measure neighborhood racial composition for the years 2013–2017; hence, we report housing stock statistics for 2008 and 2013 and, for 2018, the most recent year of data available from the Florida Department of Revenue.

neighborhoods where Hispanics are underrepresented. These results illustrate the growing importance of single-family rentals as a housing option within White neighborhoods.

In summary, SF rentals are now an important part of the rental housing market, whether measured for the nation, the state of Florida, large counties in Florida, or neighborhoods within these counties where minorities have historically been underrepresented. The impetus behind this growth in favor of rentals originated over a decade ago as bank-owned properties from the foreclosure crisis were purchased by investors and subsequently rented out. Today, the SF rental market remains strong as many households opt in favor of renting over purchasing (Joint Center for Housing Studies, 2017), and both conversions and new construction account for the supply of SF rentals.

3. Literature Review

To our knowledge, no study has investigated the effect that SF rentals have on neighborhood housing integration. There are, however, a number of studies whose results relate to the issue of whether minority families move to better neighborhoods in response to an increase in housing affordability. One set of papers investigates whether lower-income and minority families residentially relocate so that their children can attend a better school if housing within that school's attendance zone becomes more affordable (Ihlanfeldt, 2019; Ihlanfeldt and Mayock, 2018, 2019). Using data on Florida school districts, these papers are differentiated by the disadvantaged groups considered and by the measures of affordable housing and the identification strategies used. Remarkably, they share a common conclusion, namely, that placing a larger share of a district's affordable housing within better school zones reduces racial and income school segregation. A limitation of this research is that only short-run outcomes are analyzed. If the entrance of minority or lower-income families into the neighborhood or their children into the neighborhood school induces Whites to flee, the long- and short-run outcomes may be very different, and it is the long-run effect that garners the greater interest.

Evidence inconsistent with that from the above studies comes from the Moving To Opportunity (MTO) experiment (Sanbonmatsu et al., 2011) and national data on the residential locations of housing voucher recipients (Horn et al., 2014). The MTO experiment offered housing vouchers to two groups of eligible households. One group had no constraint on where they could locate, while the other group was required to locate in a low-poverty neighborhood. Interestingly, the uptake rates (i.e., the percentage of households accepting the vouchers) were low. The percentages were 63 percent and 48 percent for the locational unconstrained and constrained groups, respectively. These results suggest that many disadvantaged households may not move to better neighborhoods when the opportunity presents itself. Similar findings are provided by Horn et al. (2014). Using confidential data on the residential locations of voucher recipients from the Department of Housing and Urban Development (HUD), the authors found that the children of voucher holders are more likely to attend low-performing schools than the children of households that do not receive housing vouchers.

To investigate why housing voucher recipients do not move to "high opportunity neighborhoods," Bergman et al. (2019) conducted randomized controlled trials with housing voucher recipients in the state of Washington.[6] Their findings imply that most low-income families do not have a strong preference to stay in low-opportunity areas; instead, barriers in the housing search process are a central driver of residential segregation by income. Their results apply only to voucher recipients and may not be applicable to minorities in general.

[6] High opportunity neighborhoods are those that have been identified nationwide by Chetty and Hendren (2018) as providing upward mobility to the children from poverty families who move into these neighborhoods.

In summary, the results of some studies suggest that improved housing affordability can reduce neighborhood segregation, while others suggest that disadvantaged households do not move or locate to better neighborhoods in response to offered or accepted housing vouchers. As noted earlier, a limitation of the first group of studies is that they focus exclusively on short-run effects. In addition, only the movements of families with children are considered. Studies in the second group are limited in that only the location decisions of subsidized households are considered. Our analysis is not subject to either of these limitations. We investigate longer-run changes in neighborhood racial composition that result from an improvement in housing affordability, as captured by a neighborhood's shift in housing tenure in favor of SF rentals, where all Black and Hispanic households are included in the analysis.

4. Conceptual Framework[7]

Our focus is on neighborhoods where minorities have historically been underrepresented. An increase in single-family rentals as a percentage of the housing units within these neighborhoods may increase housing affordability allowing for greater minority access. Housing affordability can improve through two pathways—single-family rentals may emit negative spillover effects that lower the cost of housing within the neighborhood, and they may lower the cost of neighborhood entry by providing an alternative to the owner-occupied housing that predominates within these neighborhoods. The entry cost on rental housing is the security deposit and required renters' insurance, while the upfront cost of obtaining owner-occupied housing is the down payment on the mortgage and associated fees. Evidence is consistent with the idea that an increase in single-family rentals as a percentage of a neighborhood's housing units (with a corresponding decrease in the

[7] Our conceptual framework is based on a static general equilibrium model of neighborhood residential sorting developed in previous work (Ihlanfeldt and Mayock, 2018). We refer readers to this paper for a more formal theoretical model underlying our empirical work.

percentage of owner-occupied single-family homes) results in lower neighborhood housing prices (Coulson et al., 2002; Coulson and Li, 2013; Ihlanfeldt and Yang, 2021; Wang et al., 1991).[8] While the exact mechanisms underlying these negative effects have not been identified, there are at least three possibilities. In comparison to owner-occupied homes, rentals may be less well maintained and, in comparison to the owners of homes, tenants of rental units may be more likely to raise the level of neighborhood crime (because of their lower average income and wealth) and may be less committed to improving the schools, parks, and other amenities of the neighborhood.[9]

On the surface, the idea that improving housing affordability in White neighborhoods should result in a residential reshuffling of a community's minority households in favor of these areas may seem self-evident. However, there are reasons to suggest that such re-sorting may not occur. First, minorities may encounter housing market discrimination that limits their ability to take advantage of cheaper housing in neighborhoods where high percentages of Whites reside. Second, the locational decisions of minority households may be governed by other, stronger needs that keep them living within segregated neighborhoods. These include access to jobs, welfare services, or public transportation. Finally, it has been suggested that the distance of the move, especially if from one side of the urban area to the other, may be too long and arduous for some families to overcome (Ellen et al., 2016). Long distances may also limit the knowledge that minorities have of the affordable housing opportunities found within White neighborhoods. Hence, the correct

[8] Prior to transferring from owner-occupancy to a rental, a home may be vacant for a period of time. This may generate short-run neighborhood price effects that differ from those in the long run. For example, the home may have been foreclosed upon and is a vacant Real Estate Owned (REO) property. A vacant unit may have a different negative effect on neighborhood house prices in comparison to a rental. Neighborhood prices may rise when a vacant home is sold for rental, if vacant units produce greater spillover effects than do rentals. In addition, prices may rise because of a reduction in the supply of homes available for purchase (Ganduri et al., 2019).

[9] Many studies have found that rentals are less well maintained than owner-occupied housing (Galster, 1983; Gatzlaff et al., 1998; Harding et al., 2000; Shilling et al., 1991). Regarding the relationship between rentals and crime, the evidence is far less extensive, consisting only of Ihlanfeldt and Yost (2019). However, their study is particularly relevant because their data come from Miami-Dade County, which is one of the nine counties used to estimate our models. Using panel data at the neighborhood level, they find that rentals impact neighborhood crime, controlling for year and neighborhood fixed effects and the possible endogeneity of the number of rental units.

answer to the question of whether housing segregation declines in response to more affordable housing, as provided by SF rentals, within White neighborhoods is unclear, a priori.

In summary, the percentages of residents who are minorities within White neighborhoods may rise in response to a shift in housing tenure in favor of rentals if minorities move to these neighborhoods to take advantage of their lower housing costs or lower cost of neighborhood entry. However, the minority percentage may also rise because Whites, regardless of tenure, leave the neighborhood or choose not to move to the neighborhood because of the decline in neighborhood quality attributable to the SF rentals. This underscores the importance of empirically addressing not only the change in the racial composition of neighborhoods in response to an increase in their SF rental shares but also the magnitudes of the in-migration and out-migration of racial groups in possibly accounting for these results. Because single-family rentals may lower neighborhood housing prices, also of interest is whether an increase in the minority percentage of the neighborhood comes from more minority renters or homeowners, especially in light of the growing disparity in homeownership between Blacks and Whites (Choi et al., 2019).

5. Data

We define the census block group as our neighborhood unit. For each block group, the American Community Survey (ACS) reports a five-year average of the number of each racial group residing in the neighborhood. From these data, we calculated the average percentages of the neighborhood's population who are Black, White, and Hispanic. Our panel begins with the year 2008, so the first five-year average covers the years 2008–2012. In the second year of our panel (2009), the average would cover the years 2009–2013. The final year of our panel is 2013, and the average would be for the years 2013–2017. Using the county-level data from the ACS, we also computed the racial shares of the population for each five-year period. We formed three neighborhood samples based upon whether the racial group's percentage for the neighborhood using the first five-year average of the panel (2008–2012) was less than that for the county as a whole. For our nine Florida counties, there are 3,927 neighborhoods where Blacks are underrepresented, 3,407 neighborhoods where Hispanics are underrepresented, and 2,500 neighborhoods where Whites are underrepresented. The underrepresented Black and Hispanic neighborhood totals represent 70 and 60 percent of the total number of neighborhoods, respectively. These percentages highlight the high level of neighborhood racial segregation within the counties included in our sample. To investigate changes in the three groups by tenure, for each of our neighborhoods where a group is underrepresented, we obtained from the ACS the number of households by race and whether the head of the household owned or rented the home.

Our land use data come from the standardized property tax rolls that each county in the state of Florida must submit annually to the Florida Department of Revenue. These tax roll data, which are updated on an annual basis, contain a wealth of information on real property characteristics, including land use counts at the block group level broken into 83 categories. From these counts, we selected the following residential units: SF detached homes and other residential units. We also used the rolls to construct the neighborhood attributes that are ostensibly correlated with its level of attractiveness. These include the land areas of parks and vacant industrial land (measured in square miles), the aggregated square footages for commercial properties providing shopping opportunities and for other commercial properties not offering these opportunities, the aggregated square footage for industrial properties, and the number of alcohol-serving establishments other than restaurants (e.g., bars, clubs, and cocktail lounges) and the number of restaurants (excluding fast-food). Different racial groups may weigh neighborhood attributes differently in forming their impression of the quality of the neighborhood, resulting in different entry and exit rates.[10] If these differences are correlated with the neighborhood's percentage of housing units that are SF rentals, their exclusion from our estimated models may result in biased estimates of the effect of the rentals on integration. We estimate our models with and without the neighborhood attributes.

Most important for our study is a field within the tax rolls that indicates whether or not a property was granted a property tax homestead exemption. According to Florida Statute 196.031, this exemption is available to "[a] person who, on January 1st, has the legal title or beneficial title to real property in [Florida] and who in good faith makes the property his or her permanent residence or the permanent residence of another or others legally or naturally dependent upon him or her."[11] We use the absence of a homestead exemption as one condition required to classify a property as a rental. However, this may result in an overestimate of the number of SF rentals to the extent that homeowners are living in the home but fail to apply for the homestead exemption. Our second condition for identifying a rental is that there must be a difference between the address of the home and the address of the property owner.[12]

Meeting these conditions does not ensure that the unit is currently rented. However, the tax roll data are reported for January 1 of the tax roll year. A unit can satisfy our two conditions anytime in the previous 12 months. Assume, for example, the year is 2010. If the conditions were met early in 2009, the unit is unlikely to be vacant during 2010. If the conditions were met toward the end of 2009, the unit might not be rented for all 12 months of 2010, depending on the time it

[10] Boehm and Ihlanfeldt (1991) provide empirical evidence that neighborhood preferences differ among racial groups.

[11] A homestead exemption decreases a property's taxable value by as much as $75,000, resulting in annual property tax savings from $800 to $1200, depending on millage rates. It also places a cap on how much the assessed value of the home can increase annually: 3 percent or the rate of inflation, whichever is lower. The substantial reduction in the annual assessment and the tight cap on its annual growth provided by a homestead exemption make it highly worthwhile to claim for eligible homeowners.

[12] There is also the possibility that the owner takes the homestead exemption illegally and rents out the unit. Besides the penalties associated with apprehension, there would be the inconvenience of the owner's mail being delivered to the rental. Hence, we expect that this deception is uncommon.

takes for the owner to find a tenant.[13] The occupancy status of individual housing units is generally not known; however, we have some assurance that Florida's strong housing market and the aforementioned timing of events result in the vast majority of our SF rentals being occupied. Moreover, as reported below, we find no evidence of a correlation between the housing vacancy rate within a neighborhood and the number or percentage of SF rentals. Our housing typology consists of owner-occupied SF homes, SF rentals, and other housing units, which are largely units in multifamily properties (86 percent).

6. Empirical Methodology

We are interested in empirically addressing three issues with our panel of Florida neighborhoods. First, how do increases in SF rentals as a share of the neighborhood's total housing units affect neighborhoods' racial compositions?[14] We estimate separate models to determine how a shift in share in favor of SF rentals and away from SF owner-occupied housing affects 1) the percentage of the neighborhood's population who are Black in neighborhoods where Blacks have historically been underrepresented, 2) the percentage of Hispanics in neighborhoods where they have been underrepresented, and 3) the percentage of Whites in neighborhoods where they have been underrepresented. Second, to what extent are changes in these percentages the result of growth or decline in the percentages of neighborhood households of each racial group who are renters as opposed to homeowners? Third, to what extent are changes in the racial composition of neighborhoods due to differences in each of the three racial groups' net migrations? The

[13] Renter's Warehouse is a company that manages a large number of SF rentals in Florida. It reports an average of 17 days to find a tenant.

[14] Another question that could be addressed is whether an increase in the neighborhood's share of condominium rentals results in more racial integration. We choose not to investigate this issue because condominiums in Florida are frequently second homes not available as permanent rental units. Our method of identifying a unit as a rental would, therefore, potentially result in a high level of miscategorization.

neighborhood composition models, the household renter and owner models, and the migration models are described in subsections 6.1, 6.2, and 6.3, respectively.

6.1. Neighborhood Racial Composition Models

To explain the share of Blacks as a percentage of a neighborhood's residents within neighborhoods where they have been underrepresented (relative to their share of the county's population), we regressed the percentage of Blacks (measured from the ACS as an average over the years $t = 1$ to $t = 5$) on the $t = 1$ shares of the neighborhood's housing stock represented by SF rentals and other, non-SF housing units (OHUs). For example, for the first year of our panel (2008), percent Black of the neighborhood is measured as the five-year average (2008–2012) obtained from the ACS 5-year estimates, and the housing shares are computed for January 1 of 2008 from the property tax rolls. Then for the second year of the panel (2009), percent Black is measured over the years 2009–2013, and the housing shares are for January 1, 2009. SF owner-occupied housing serves as the reference housing type and is excluded from the model. Similar models are estimated to explain the percentages of Hispanics and Whites in neighborhoods where they have been underrepresented. Formally, our neighborhood composition models can be expressed as:

$$y_{it} = \boldsymbol{s}_{it}'\boldsymbol{\beta} + \boldsymbol{x}_{it}'\boldsymbol{\delta} + \alpha_i + \theta_t + \varepsilon_{it}, \quad (1)$$

where i denotes the i^{th} neighborhood (block group) and t the time index, for $i = 1, 2, \ldots, N$, and $t = 1, 2, \ldots, T$, where $T = 6$. The dependent variable y_{it} is the five-year average covering years t through $t + 4$ of the percentage of Blacks (or the percentage of Hispanics or Whites) residing in neighborhood i in year t. $\boldsymbol{s}_{it} = (s_{it,1}, s_{it,2})'$ represents the possibly endogenous SF rental and OHU housing shares measured for neighborhood i for January 1 of year t, with the associated vector of coefficients $\boldsymbol{\beta}$. $\boldsymbol{x}_{it}$ is the vector of nonresidential land uses hypothesized to affect the perceived attractiveness of the neighborhood with the associated parameters $\boldsymbol{\delta}$. α_i represents the unobserved time-invariant neighborhood-specific heterogeneity, which can be correlated with all explanatory variables. θ_t signifies the year fixed effects. ε_{it} is the idiosyncratic time-varying error component.

Although we include neighborhood fixed effects to control for unobservable time-invariant heterogeneity affecting the racial composition of the neighborhood, there may be time-varying unobservables that are correlated with the shares of SF rentals (*SFR%*) or OHUs (*OHU%*) that have their own impact on the racial percentages represented by our dependent variable. Hence, to test and, if necessary, to control for this possibility, we need instrumental variables (IV) for the housing shares that satisfy strict exogeneity (i.e., variables that are correlated with the housing shares that would not have their own influence on the racial percentage in all periods). Conceptually, it is reasonable to argue that a change in *SFR%* or *OHU%* is driven by factors both within the neighborhood and countywide. While factors within the neighborhood may be endogenous to the racial percentage, countywide factors should not be affected by conditions within the home neighborhood, especially if the countywide factors are defined over the portion of the county that excludes the home neighborhood. Based on this logic, we suggest the following IV: first, define a base year preceding the beginning of the panel. Using the entire county, then calculate the percentage change in the share of the housing type at the county level between the base and current years, excluding the home neighborhood value. Then multiply these percentage changes by a base year value of the housing share to obtain a prediction ($\hat{s}$), assuming the growth in the share at the neighborhood level followed the change that occurred at the county level. Formally,

$$\hat{s}_{it} = s_{ib} \times \left(1 + \frac{s_{ct} - s_{cb}}{s_{cb}}\right), \qquad (2)$$

where i indexes the neighborhood, t indexes the current year, b is the base year, and c represents the county (excluding neighborhood i).[15] Note that by construction, the IV varies over time, across counties, and over neighborhoods within counties. While the racial percentage may affect s_{it}, it should not have an effect on $\hat{s}_{it}$. However, the validity of $\hat{s}_{it}$ as an instrument also depends on whether the neighborhood base year housing share can be treated as exogenous. For example, there may be an omitted variable that is correlated with the base year value that has a delayed impact on neighborhood quality, which in turn affects the racial percentage. In that case, the instrument would, in part, capture the omitted variable effect and would not be orthogonal to the error term of our estimated equations. The way to guard against this is to move the base year backward in time, lessening the probability that a delayed response could impact the current year's neighborhood racial percentage. We went back a full decade to obtain our base year housing share values (1998).[16] It is highly unlikely that the housing shares or their correlates measured ten years prior to the beginning of our panel would affect the current year's racial percentages, conditional on including the current year shares as explanatory variables. As we report below, based on both logic and test results, we treat *SFR%* as endogenous (using $\hat{s}_{it}$ as the instrument) and *OHU%* as exogenous in estimating our neighborhood racial composition models.

[15] Because we define a base year in constructing our instrumental variable, it might be confused with shift-share instruments pioneered by Bartik (1991), who used industry shares for a base year and national growth rates to construct a shock to local labor demand. Our instrument has little in common with these instruments. The key assumption underlying our instrument is that changes in the share of housing units within the county represented by SF rentals will impact the change that occurs in the SF rental share within a small area (the block group) within the county. Beyond county-level changes in the demand for these rentals, Florida is a growth management state, where changes in land use are affected by the comprehensive plans that each county is legally required to have.

[16] The tax rolls from the Florida Department of Revenue are available for the years 1995–2018. Although our six-year panel only uses rolls from 2008 to 2013 (in order to match up with the ACS data), we also obtained the tax rolls for 1998 to form our instrumental variable.

6.2. Neighborhood Household Tenure Models

The owner and renter models are similarly structured to the neighborhood racial composition models. The explanatory variables are identical, year and neighborhood fixed effects are included, and SF rentals are again instrumented using $\hat{s}_{it}$; however, the dependent variable is now the percentage of neighborhood households who are members of a particular racial and tenure group. For example, we separately estimate the percentage of households who are Black renters and who are Black homeowners. A total of six models are estimated (i.e., renter and homeowner models for each racial group).[17]

6.3. Neighborhood Migration Models

To address the roles played by the neighborhood entry and exit of different racial groups in accounting for the change in neighborhood racial composition resulting from an increase in *SFR%*, we estimated models that held constant the number of two of the three racial groups at their initial (2008) values, allowing changes in the third group to drive the percentage change. For example, to assess the relative importance of Black entry in comparison to White and Hispanic exit in explaining an increase in percent Black, we estimated a set of three models with the following dependent variables:

$$B_t/(B_t + \bar{H} + \bar{W}), \quad \text{Black effect} \tag{3}$$

$$\bar{B}/(\bar{B} + H_t + \bar{W}), \quad \text{Hispanic effect} \tag{4}$$

$$\bar{B}/(\bar{B} + \bar{H} + W_t), \quad \text{White effect} \tag{5}$$

[17] One difference between the racial composition and housing tenure models is that the ACS does not provide a tenure breakdown for non-Hispanic Blacks at the household level; hence, Black households include Hispanics who identify their race as Black. However, only a small percentage of Hispanics identify as Black.

The right-hand side variables are the same as in equation (1), with *SFR%* again instrumented with $\hat{s}_{it}$. A bar above the variable indicates the number of the racial group is being held constant at its initial value. While the coefficients on *SFR%* estimated from these equations do not provide a precise decomposition of entry and exit effects, they show the main driver or drivers underlying the impact of a change in *SFR%* on the percentage of the neighborhood's residents who are Black. A similar set of models is estimated to assess the importance of racial migratory movements in accounting for the effect of *SFR%* on the percent Hispanic and percent White of the neighborhood.[18]

7. Results from Estimating the Neighborhood Composition Models

Tables 3–5 present the results from estimating our percent Black, percent Hispanic, and percent White equations using as observations all neighborhoods where each group is underrepresented.[19] For each housing share explanatory variable, three numbers are given: the estimated coefficient, the cluster-robust standard error (in parentheses),[20] and the change in the dependent variable induced by a within-neighborhood standard deviation change in the variable, holding all other variables constant (in brackets).[21] As described in Section 6, *SFR%* is treated as endogenous in the models we estimate.[22] We chose to treat the share of OHUs (*OHU%*) as

[18] To be clear, when we refer to entry (exit), we mean that the 5-year average of the number of the group increased (decreased); that is, on average, the number entering was greater than (less than) the number leaving. We make no allowance for births and deaths, so there is some random error in our entry and exit measures.

[19] Although the estimated models include the nonresidential neighborhood descriptors as control variables, only the results obtained with the housing share variables are reported in the tables. Complete results are in Appendix Tables A.1—A.3.

[20] Although the outcome variables are serially correlated, the standard errors clustered at the block group level are robust to arbitrary serial correlation within a block group (see, for example, Arellano, 1987; Bertrand et al., 2004; Cameron and Miller, 2015; Wooldridge, 2010, Section 20.3). The clustered standard errors are also robust to unknown heteroskedasticity. Also relevant to our standard error estimates is that the ACS data at the block group level tend to have relatively large margins of error; however, these errors are unlikely to be correlated with our explanatory variables (and instruments), which are from a different data source. Therefore, our estimates remain consistent, although less precise than with perfect data, reflected in larger standard errors.

[21] Because we are using panel data, a standard deviation change can be computed between two randomly selected neighborhoods or between two randomly selected years within the same neighborhood. We use the within-neighborhood change rather than the between-neighborhood change because it is the more conservative number and has the more meaningful policy interest.

[22] The first stage and reduced-form estimates are reported in an online supplement, which is available at https://sites.google.com/site/cynthiafanyang/research.

exogenous. These units are almost always located in multifamily buildings. An annual increase in these units comes mostly from new construction. The length of time between the decision to build and occupancy is very long for these properties. Finding and purchasing the land (sometimes involving assembling multiple parcels), completing the building and site plans, obtaining project approval from local government (multiple levels of government are often involved), and demolition/construction all together commonly take years in the making. Hence, we do not expect the current racial mix of the neighborhood or time-varying within tract unobservables would impact the current *OHU%*. SF rentals, however, are different. Whether suppliers are builders or converters of existing owner-occupied homes, neighborhood house values may play a role in their decisions. Moreover, the time involved in creating a rental from a previously owner-occupied home can be short in duration. The construction of a new home takes more time, but in most cases, it also is of short duration, given that builders typically build on developed lots with permitting already in place.

Our decisions to treat *OHU%* as exogenous and *SFR%* as endogenous are supported by the results from conducting an endogeneity test. Our test is based on the *C* statistic, which is defined as the difference of two Sargan-Hansen statistics: one for the equation with the regressor treated as endogenous and one for the equation where the regressor is treated as exogenous.[23] The null hypothesis is that the regressor is exogenous. The test's reliability hinges upon the validity of our instrumental variable, which in turn depends on satisfying two conditions—the instrument is strictly exogenous and not "weakly" correlated with the tested regressor. Our theoretical argument in favor of exogeneity was made above in the description of our empirical methodology. The endogeneity test requires that both *OHU%* and *SFR%* be treated as endogenous. For models with

[23] The test statistic is obtained by specifying the endog option in Stata ivreg2 and robust to clustering; it is numerically equal to a Hausman test statistic under conditional homoskedasticity.

multiple endogenous variables, Baum et al. (2003) have illustrated that the standard *F* statistic may not be sufficiently informative. A more informative test is the Sanderson-Windmeijer (SW, 2016) conditional *F* statistic that tests the weak identification of individual endogenous regressors. This statistic is constructed by "partialling-out" linear projections of the remaining endogenous regressors. Again, we use an SW *F* value of 10 or greater to reject that our instrument is weak.[24] The standard *F* and the SW *F* statistics are all over 100, providing strong evidence that our instruments are not weak. For *OHU%*, the null hypothesis of exogeneity cannot be rejected at a high level of confidence (for example, for the percent Black model, the *p*-value=0.656). For *SFR%*, the null hypothesis is also rejected with a high level of confidence (*p*-value=0.003 for the percent Black model).

Table 3 reports the percent Black results. For the sample of all neighborhoods where Blacks are underrepresented (column 1), an increase in *SFR%* is found to have a positive and highly significant effect (*p*-value=0.000) on the percentage of residents who are Black. The estimated coefficient is 0.537, and a within-neighborhood standard deviation increase in the share increases percent Black by a little more than one percentage point. To gauge whether these estimated effects are reasonable and carry any economic significance, consider the median neighborhood among the Black underrepresented neighborhoods used to estimate the model. The Black share of the median neighborhood is 2 percent. Our estimate implies that the impact on percent Black from a within-neighborhood standard deviation increase in *SFR%* (which equals about 16 rentals) raises percent Black from 2 to 3 percent. We assess this change as both plausible and economically important.

[Table 3 about here]

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[24] We again consider the robust SW *F* statistic. However, we caution that its theoretical link to the Stock-Yogo (SY, 2005) critical values, which assume homoskedastic serially uncorrelated errors, is still an open question. The use of SY critical values results in a conservative test that rejects the null of weak instruments too infrequently when the null is true. Therefore, we employ the rule-of-thumb value of 10, which is higher than the SY critical values in the case of just-identified models with multiple endogenous variables.

While our overall finding is important, it becomes more or less so depending on the quality of the neighborhood. The final three columns of Table 3 report the results from estimating equation (1) for low-, middle-, and high-income neighborhoods, which are defined separately for each county.[25] For low- and middle-income neighborhoods, an increase in *SFR%* is found to raise percent Black, and each effect is significant at the 5 percent level or better. For high-income neighborhoods, the estimate is marginally insignificant at the 10 percent level. Unsurprisingly, the size of the effect falls with the neighborhood income level: low income (0.930), middle income (0.464), and high income (0.401). As income increases, the affordability of the rent on the SF rentals is expected to decline, reducing the number of minorities able to move into the neighborhood. Nevertheless, there is still an important effect within middle-income neighborhoods, where a within-neighborhood standard deviation increase in *SFR%* is again found to cause a one percentage point increase in percent Black.

Table 4 reports the results obtained for the percent Hispanic models, which contrast to those obtained for percent Black. In neighborhoods where Hispanics are underrepresented, an increase in *SFR%* is found to decrease the percentage of neighborhood residents who are Hispanic (−0.539, *p*-value=0.010). The separate models estimated for each neighborhood income group show that this negative finding is restricted to low-income neighborhoods (−0.738, *p*-value=0.002). In the middle- and high-income neighborhoods, *SFR%* has no statistically significant effect on percent Hispanic.

The interpretation of our results for Hispanics is hampered by not knowing their origins, which unfortunately is not provided at the block group level by the ACS. For our sample of nine counties, three groups represent 71 percent of the total number of Hispanics: Cubans (34.5%), South

[25] For each county, the low-, middle-, and high-income neighborhood cutoffs are obtained at the county level for the first year of our panel by examining the distributions of neighborhood median incomes.

Americans (20.0%), and Puerto Ricans (16.3%). Ideally, separate racial composition models would be estimated for each group. Income data on these groups is further limited to the national level, which shows large differences in household incomes, especially lower incomes for Puerto Ricans (Pew Research Group, 2019). Our finding that an increase in *SFR%* reduces the Hispanic percentage only within low-income neighborhoods where Hispanics are underrepresented may be registering an origin effect, as well as an income effect.

[Table 4 about here]

Greater neighborhood integration from an increase in *SFR%* may come from an alternate source, other than from minorities moving to neighborhoods where they have historically been underrepresented. Whites might respond to the SF rentals by moving to neighborhoods where they are underrepresented. However, because there is strong evidence that Whites have an aversion to living in minority neighborhoods (Krysan et al., 2017; Krysan et al., 2009), we viewed this alternative source of integration as unlikely. However, for completeness, we estimated percent White equations for neighborhoods where Whites have historically been underrepresented. Another motivation for estimating these models is that they provide a placebo test of the results we found for Blacks. If SF rentals register an important effect in these models, this would call into question the results obtained for Blacks. The results shown in Table 5 confirm our expectations. For all neighborhoods and neighborhoods of different incomes, the estimated effect of *SFR%* on percent White is trivial in magnitude and not statistically significant.

[Table 5 about here]

As a final cut of the data, we divided neighborhoods into two types based on the race of the dominant reference group. For example, for percent Black two separate models were estimated—one for neighborhoods where the White population was larger than the Hispanic population (White neighborhood), and one for neighborhoods where Hispanics outnumbered Whites (Hispanic neighborhood). Similarly, percent Hispanic models are estimated for Black and White neighborhoods and percent White for Black and Hispanic neighborhoods. Discrimination or prejudice on the part of one racial group against the others may have a bearing on our results. The results for the housing shares are presented in Table 6. Appendix Table A.4 reports complete results including the nonresidential controls.

Whether the neighborhood is White or Hispanic has little influence on the effect that *SFR%* has on percent Black. The estimated coefficients for the two types of neighborhoods are positive and significant, equaling 0.552 (*p*-value=0.030) and 0.597 (*p*-value=0.001), which are close to the effect obtained without stratifying the sample (0.537). For percent White, *SFR%* is not significant regardless of whether the neighborhood is Black or Hispanic, matching full sample results. For percent Hispanic, the effects do differ between Black and White neighborhoods. While the effect is negative and significant for Black neighborhoods (−1.036, *p*-value=0.008), it is insignificant for White neighborhoods.[26]

[Table 6 about here]

All of the neighborhood composition models include the nonresidential neighborhood descriptors as control variables. Generally, more than one of the variables is statistically significant at the 10 percent level in every model, and as a group, they are also jointly significant. The significant variables differ among the three racial groups. Vacant industrial land reduces percent

[26] A reviewer suggested that it is also of interest to know if neighborhoods that lose SF rentals also regress on measures of integration. To this end, we investigated whether an increase in *SFR%* and a decrease in *SFR%* have asymmetric effects on integration. We find no asymmetric effects in all specifications of the composition models, whether or not the nonresidential controls are included. This conclusion was reached by estimating the first-difference (FD) fixed effects models in which the FD of *SFR%*, denoted by Δs_{it}, was split into $\Delta s_{it}^{+} = (s_{it} - s_{i,t-1})I(s_{it} > s_{i,t-1})$ and $\Delta s_{it}^{-} = (s_{it} - s_{i,t-1})I(s_{i,t} \leq s_{i,t-1})$, where $I(\cdot)$ is the indicator function. The rental shares were instrumented by $\Delta \hat{s}_{it}^{+}$ and $\Delta \hat{s}_{it}^{-}$ defined similarly. We performed a Wald test on whether the coefficients on Δs_{it}^{+} and Δs_{it}^{-} are the same. The null hypothesis cannot be rejected at the 5% level in all cases. These results are available upon request.

Black for all neighborhoods and neighborhoods categorized by their income level. More restaurants increase percent Black for all and low-income neighborhoods. The variables mostly affect the Hispanic percentage within low- and middle-income neighborhoods, where more industrial space, park land, and vacant industrial land have positive effects. Alcohol-serving establishments consistently are found to reduce the White percentage. While these results indicate that the nonresidential variables matter to the racial composition of neighborhoods, excluding them from the models has little effect on the estimated effects of *SFR%*. There are only small changes in these estimates, with no changes in their levels of statistical significance.[27]

8. Results from Estimating the Neighborhood Household Tenure Models

The results from the neighborhood racial composition models reported in the previous section suggest that SF rentals affect the racial mix of neighborhoods. In this section, the level of our analysis shifts from the individual to the household. The advantage is that the ACS identifies the housing tenure of households, and this affords an opportunity to investigate whether changes in the racial mix of neighborhoods attributable to an increase in *SFR%* come from renters or homeowners. As described in Section 6.2, the models are identical to the composition models, except the dependent variables are the percentage of the neighborhood's households represented by a race and tenure (e.g., the percentage of households who are Black renters). To check whether our results are robust to measuring the racial mix of the neighborhood at the household rather than individual level, we also report regressions where race is not broken down by tenure (e.g., the dependent variable is the percentage of households who are Black). The neighborhoods for each racial group are again those where the group has historically been underrepresented. A condensed summary of our results is in Table 7. Complete results are in Tables S.9—S.14 in the online

[27] See Tables S.15—S.18 in the online supplement for the results obtained excluding the nonresidential control variables.

supplement. The top row of Table 7 reports the results for each racial group without the tenure breakdown. They mirror the results in Tables 3–5: an increase in *SFR%* increases Blacks, decreases Hispanics, and has no effect on Whites as percentages of households within neighborhoods where each group is underrepresented. The tenure breakdown for Blacks shows that an increase in *SFR%* increases Black renters but not Black homeowners as a percentage of the neighborhood's households. In contrast, for Hispanics, a larger *SFR%* decreases renters and increases homeowners as percentages of a neighborhood's households. Without data following individual households, we cannot identify the extent to which the Hispanic results reflect tenure switching within the neighborhood. A possible explanation for the increase in Hispanic ownership is that the SF rentals produce negative spillover effects that lower neighborhood housing prices. In the case of Whites, *SFR%* induced changes in the rental percentage are close to nil and insignificant. While there is a negative change in the owner percentage, it is significant at only the 10 percent level.

[Table 7 about here]

9. Results from Estimating the Neighborhood Migration Models

Our final set of findings are from the estimation of our migration models to assess the racial group migrations into and out of the neighborhood that may underlie the changes in neighborhood racial composition resulting from an increase in *SFR%*. There are three possible effects, which are labeled from equations (3), (4), and (5) the Black effect, the Hispanic effect, and the White effect. Table 8 reports on the migrations that account for the increase in percent Black from an increase in *SFR%*. For the full sample of neighborhoods where Blacks are underrepresented, the Black effect is 0.510 and is highly significant (*p*-value=0.002), while Hispanic and White effects are small and not significant. Hence, the results suggest that the increase in neighborhood racial integration from an increase in *SFR%* is driven by Black entry and not the exit of the other two racial groups.[28] This same conclusion applies to middle- and high-income neighborhoods. For low-income neighborhoods, both the Black and Hispanic effects are positive and significant, indicating that both Black entry and Hispanic exit account for the increase in integration from an increase in *SFR%*. However, the Black effect is 4.5 times larger than the Hispanic effect suggesting that Black entry rather than Hispanic exit is by far the dominant factor.

[Table 8 about here]

The results from estimating the migration models to uncover the relative importance of the three effects in accounting for the impact that an increase in *SFR%* has on percent Hispanic are reported in Table 9. For low-income neighborhoods, the Black and White effects are small and not significant, while the Hispanic effect is negative (−0.521) and highly significant (*p*-value=0.008). Although not reported in the table, the same results are found for Black neighborhoods: The Hispanic effect equals −0.735 (*p*-value=0.007), while the other two effects are not significant. These results suggest that it is the exit of Hispanics from low-income and Black neighborhoods in response to an increase in *SFR%* that accounts for the negative effect of the rentals on percent Hispanic.

[Table 9 about here]

Finally, we estimated the White, Black, and Hispanic effects that account for our estimates of an increase in *SFR%* on the White percentage within neighborhoods where they are underrepresented. Because the latter estimated effects are small and insignificant, we did not

[28] It is important to note that an increase in the net migration of Blacks into the neighborhood can increase Blacks as a share of the neighborhood population, without white or Hispanic net migration out of the neighborhood because these neighborhoods are growing in population.

expect the migration models to yield any significant results. As reported in Table 10, this is what we found.[29] [30]

[Table 10 about here]

10. Robustness Checks

We altered variable definitions and the specifications of our estimated models in the interest of testing the robustness of our results. First, we investigated whether one of the nine counties was having a disproportionate influence on our percent Black results. We dropped each of the counties one at a time from our neighborhood samples and reran the model with eight counties. *SFR%* is positive and significant in all cases, with a range in estimates from 0.4 to 0.6.[31] Recall that the estimate obtained from using all nine counties equaled 0.537. Second, we conducted the same county exclusion experiment analyzing the negative effect of *SFR%* on percent Hispanic within low-income neighborhoods (−0.738). In all cases, the effect is significant, with a range in estimates of −0.5 to −1.0. Third, we tested whether the results are sensitive to alternative constructions of the variables. Specifically, instead of basing our definition of a rental on our two conditions—that the property has no homestead exemption and the property owner's address is different from that of the rental—we just used the absence of a homestead exemption. We also reconstructed our instrumental variable, retaining the home neighborhood value in computing the county-level

[29] There is one exception. Within low-income neighborhoods where whites are underrepresented, an increase in *SFR%* raises the number of Blacks coming into the neighborhood.

[30] An alternative approach to studying the entry/exit of the racial groups in accounting for our findings from estimating the racial composition models is to estimate count models, where the dependent variables would equal the number of each racial group. While these models are less informative than our migration models in judging the relative importance of entry/exit, we estimated these models as a check on our migration model results. All of the results from estimating the latter models are consistent with those obtained from our migration models. We could have also estimated Poisson regression models for count data. However, standard IV methods cannot be easily applied; instead, a control function approach may be adopted, but bootstrapped standard errors are needed for correct inferences. Therefore, we opted for the 2SLS framework.

[31] At the suggestion of a reviewer, we also ran our neighborhood composition models only for neighborhoods within the Miami-Dade metropolitan area. The results are highly similar to those reported in Tables 3–5. For the percentage Black model, the *SFR%* estimate is 0.522 (*p*-value=0.002) and the estimate in Table 3 is 0.537 (*p*-value=0.000). For the percentage Hispanic model, the *SFR%* estimate is −0.654 (*p*-value=0.100) and the estimate in Table 4 is −0.539 (*p*-value=0.100). Both of the estimates for the white percentage are insignificant.

changes. These alterations had almost no effect on our results. Fourth, we inspected whether the results are robust to including the predicted share of SF owner-occupied homes as an additional instrument for *SFR%*. We constructed this additional IV in the same way as equation (2) by assuming that the SF owner-occupied share would grow at the county-level rate from the base year. Using both the predicted shares of rentals and owner-occupied homes as IVs has the benefit of allowing us to conduct an overidentification test and further examine the validity of our IV. For the percent Black and percent Hispanic models, the overidentification test yields Hansen *J* statistics of 0.044 (*p*-value=0.834) and 2.68 (*p*-value=0.102), supporting the validity of our instruments (i.e., that they are uncorrelated with the error term and correctly excluded from the estimated equation).

While the results obtained with *OHU%* may not qualify as a robustness check, they add credence to the results we find for SF rentals. For the percent Black equations, a shift in the share of a neighborhood's housing units in favor of OHUs, which are units within multifamily buildings, and away from SF owner-occupied housing increases the percentage of the neighborhood's residents who are Black. This holds for all neighborhoods and for all three neighborhood income groups. This percentage rise, based on the results from the estimation of the migration models, is the result of Black entry and not non-Black exit.[32] Because units in multifamily buildings are generally more affordable than owner-occupied SF homes, based on our SF rental results, we would expect OHUs to allow more Black entry into the neighborhood, assuming Blacks do not have a preference for only affordable SF homes. As shown in Table 3, both *SFR%* and *OHU%* have a positive and highly statistically significant effect on the Black percentage of the neighborhood. However, a one percentage point increase in share has a much larger impact

[32] The OHU results from our migration models are not reported in the tables but are available upon request.

(roughly six times in magnitude) on the Black percentage if the increase is in SF rentals in comparison to other housing units. This suggests that Black households have a relatively strong preference for SF rentals over multifamily units within White neighborhoods. This adds to the salience of our study. Not only are SF rentals increasing in share within White neighborhoods they also have a large impact on integrating White neighborhoods in comparison to multifamily housing options, which have been the focus of most housing affordability programs.

As another check on our results, we regressed the vacancy rate of the neighborhood (again using the ACS 5-year estimates) on *SFR%* and *OHU%*, using the same specification as in our other models (i.e., including year and neighborhood fixed effects and the nonresidential covariates, and treating *SFR%* as endogenous). If a relationship is found between the SF rentals and the vacancy rate, this would suggest that we are including vacancies among the SF rentals, introducing measurement error and possible bias into our estimated models. Separate models were estimated for all neighborhoods and the groups of neighborhoods identified where each racial group is underrepresented. In all cases, SF rentals are statistically insignificant, with low *p*-values, especially for neighborhoods where Blacks (*p*-value=0.847) and Hispanics (*p*-value=0.935) are underrepresented.[33]

11. Conclusion

In this paper, our interest was in whether an increase in a neighborhood's share of housing units represented by SF rentals results in a more racially integrated neighborhood. Contributing to this interest is the growth in SF rentals, which are now the largest segment of the rental market by valuation and households served. We offered a conceptual framework for why re-sorting across neighborhoods might occur in response to changes in these SF shares. SF rentals lower the cost of

[33] Our vacancy model results are available upon request.

neighborhood entry, and by emitting negative spillover effects lower neighborhood housing prices. To address this issue empirically, we employed a large sample of Florida neighborhoods drawn from all parts of the state to estimate the impact that an increase in the neighborhood share of SF rentals has on the neighborhood's racial composition. Our key finding is that a larger share of SF rentals results in a nontrivial increase in the percentage of the neighborhood's residents who are Black within neighborhoods where Blacks have historically been underrepresented, leading to greater neighborhood racial integration. The rise in integration is found to come from the Black entry of renters (not homeowners) and not the exit of Whites or Hispanics.

From a policy perspective, our results have considerable importance. Chetty and Hendren's (2018) findings provide support for place-focused approaches to improving economic opportunity. Without providing specific policies, they suggest two alternative strategies: helping families move to opportunity or making place-based investments. The implication that can be drawn from our findings is that moving to opportunity for Black families can be enhanced by providing more SF rental units within higher-quality neighborhoods. A possible problem in pursuing this approach is that there may be opposition from homeowners who are concerned that SF rentals will depress the values of their homes. Extant evidence tends to support this concern. In some cases, these concerns have resulted in local governments intervening in the housing market to limit the number of SF rentals (Coulson and Wommer, 2019; Dewan, 2013). Hence, if housing policy is directed toward expanding SF rentals in higher-quality neighborhoods, the opposition to SF rentals on the part of homeowners will need to be addressed.

Our findings for Hispanics contrast to those obtained for Blacks. An increase in the SF rentals share does not positively affect the percentage of a neighborhood's residents who are Hispanic within neighborhoods where Hispanics have historically been underrepresented. An increase in the SF rentals share within low-income and Black neighborhoods is found to reduce the percentage of Hispanics, which is shown to be driven by the exit of Hispanics from the neighborhood. A limitation of our analysis is that Hispanics are not treated differently depending on their origin.

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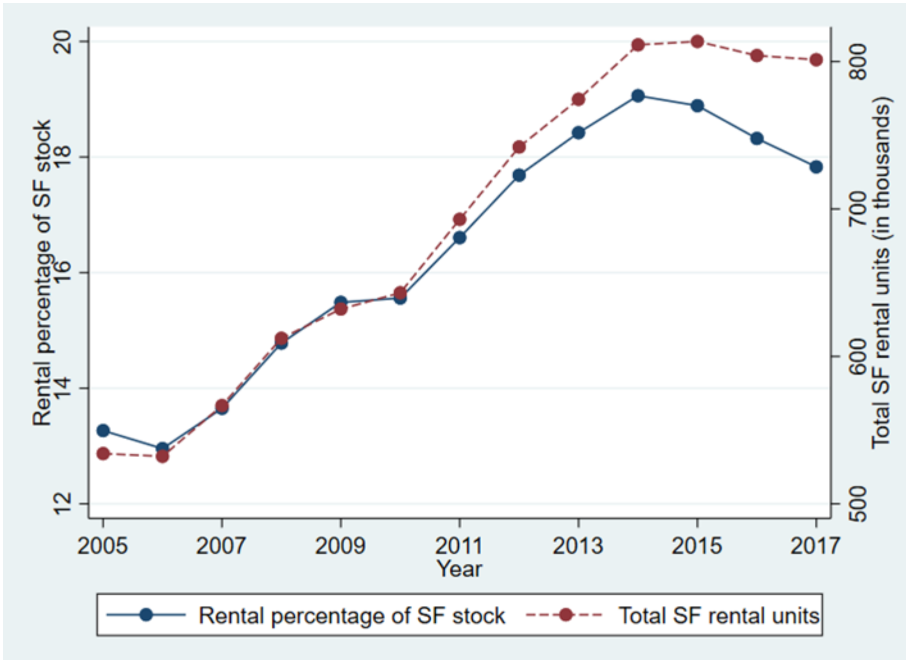
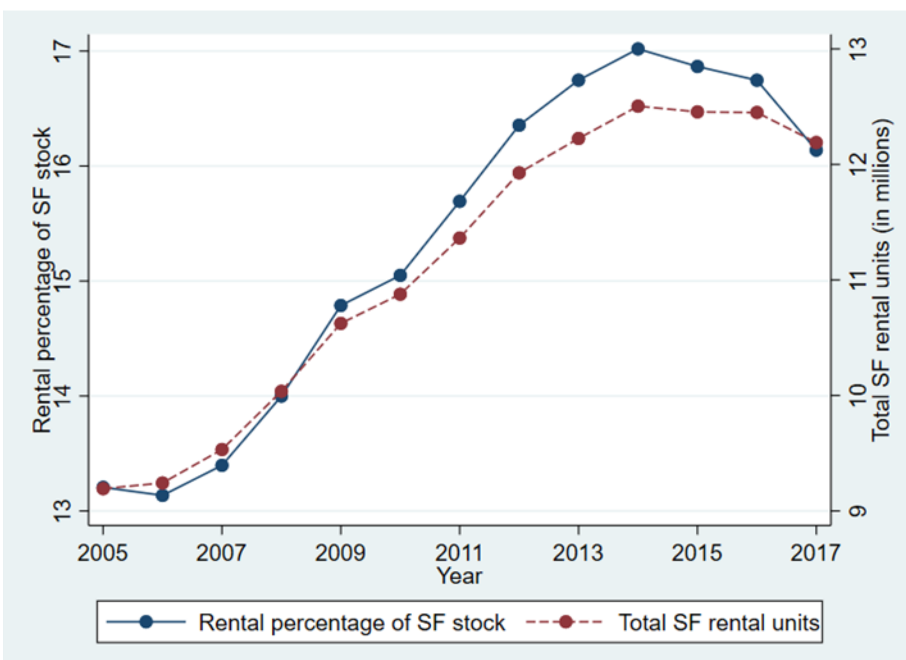
Figure 1 Rental percentage of SF stock and total SF rental units for the U.S.



Notes: Figure is produced from authors' calculations of data from the American Community Survey.

Figure 2 Rental percentage of SF stock and total SF rental units for Florida



Notes: Figure is produced from authors' calculations of data from the American Community Survey.

Figure 3   Map of neighborhoods in our sample

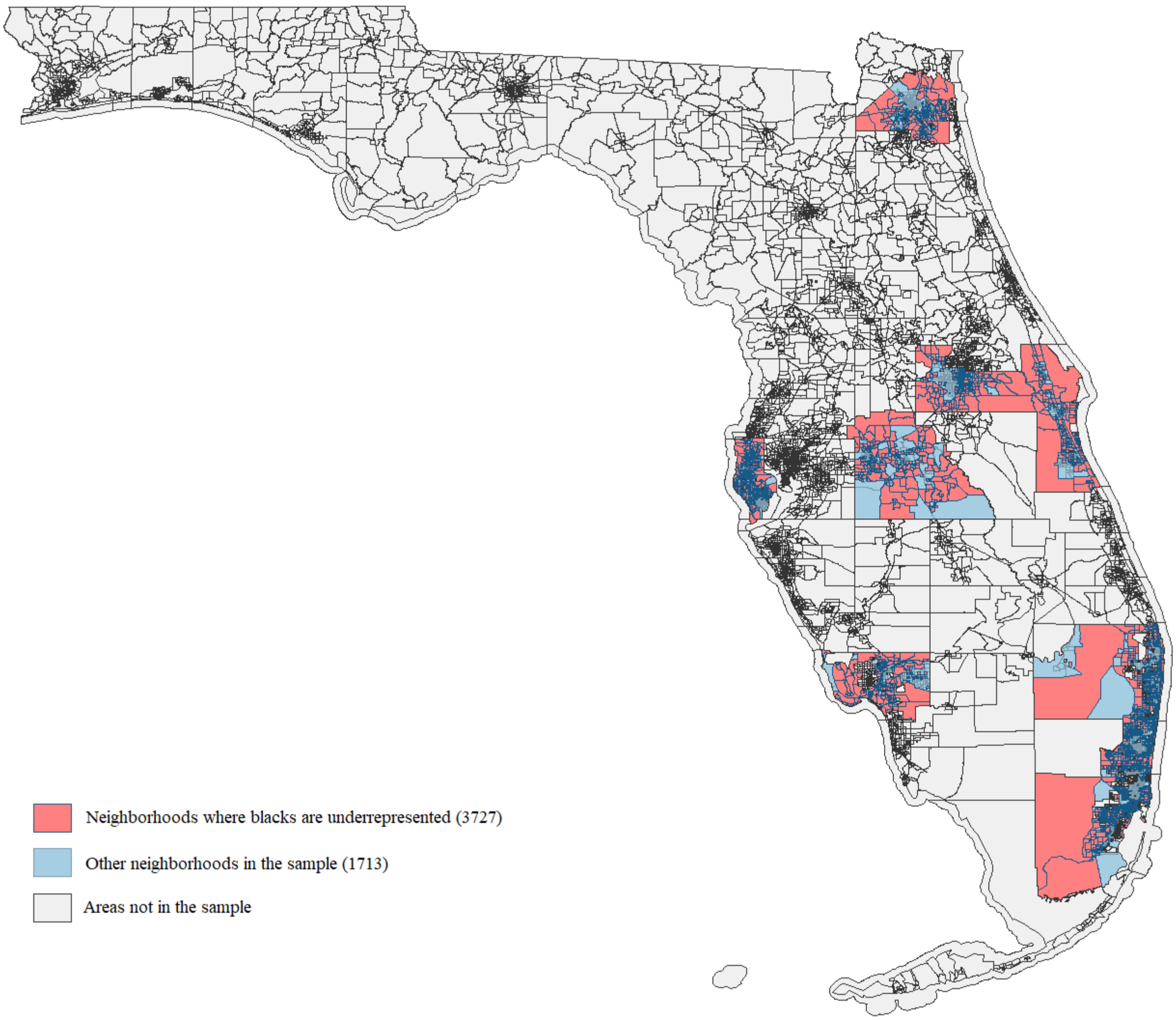


Table 1
Total Number of Single-Family Rentals, Single-Family Rentals as a Percentage of All Single-Family Housing, and Single-Family Rentals as a Percentage of All Housing Units

	All	Brevard	Broward	Duval	Lee	Miami-Dade	Orange	Palm Beach	Pinellas	Polk
Total Number of Single-Family Rentals (in thousands)										
2008	350.07	30.56	44.07	37.75	55.15	28.38	47.12	27.97	39.57	39.49
2013	490.69	37.46	64.97	49.87	65.48	46.02	63.38	66.50	51.10	45.91
2018	504.33	45.58	63.33	57.91	61.11	52.06	66.43	67.39	48.25	42.24
Single-Family Rentals Share of Single-Family Housing										
2008	15.9	17.3	11.9	15.5	28.0	9.1	17.1	13.0	16.1	24.8
2013	20.2	20.7	17.3	19.9	32.4	12.4	22.1	18.9	20.7	28.1
2018	20.0	24.3	16.6	22.1	28.1	13.8	21.3	18.6	19.4	25.6
Single-Family Rentals Share of All Housing Units										
2008	8.2	12.2	5.7	10.3	16.7	3.1	12.7	4.5	8.8	19.5
2013	11.0	14.6	8.4	13.0	19.4	4.9	13.7	10.7	11.6	19.2
2018	10.8	17.3	8.0	14.4	17.0	5.3	13.0	10.4	10.4	17.7

Table 2
Total Housing Units, Single-Family Rentals, and Housing Units Other than Single-Family Homes in Neighborhoods Where Blacks (Panel A) and Hispanics (Panel B) are Underrepresented

Panel A: Neighborhoods where Blacks Are Underrepresented										
	All	Brevard	Broward	Duval	Lee	Miami-Dade	Orange	Palm Beach	Pinellas	Polk
Total Number of Housing Units (in thousands)										
2008	2879.13	176.51	523.76	201.03	169.31	596.00	286.90	422.52	348.71	154.39
2013	2974.38	181.44	527.18	216.78	173.15	605.74	331.08	425.41	354.09	159.51
2018	3123.33	184.43	542.57	232.46	186.48	628.64	374.11	443.45	360.44	170.75
Total Number of Single-Family Rentals (in thousands)										
2008	204.12	18.34	26.68	15.80	22.63	15.51	34.75	16.70	28.25	25.47
2013	291.50	23.17	38.92	22.31	27.62	24.53	46.85	40.94	37.03	30.12
2018	299.36	28.03	37.57	25.50	26.57	28.00	48.83	41.22	34.46	29.17
Total Number of Other Housing Units (in thousands)										
2008	1430.52	57.70	273.04	57.91	79.79	403.26	73.88	282.66	154.94	47.34
2013	1363.15	58.82	271.87	67.76	80.13	375.16	106.86	195.08	158.51	48.97
2018	1442.70	58.99	283.08	74.25	84.57	394.52	129.03	203.96	162.91	51.39
Single-Family Rentals Share of Single-Family Housing										
2008	14.09	15.44	10.64	11.04	25.28	8.05	16.31	11.94	14.58	23.79
2013	18.09	18.89	15.24	14.97	29.69	10.64	20.89	17.77	18.94	27.24
2018	17.81	22.34	14.48	16.12	26.07	11.96	19.93	17.21	17.44	24.44
Single-Family Rentals Share of All Housing Units										
2008	7.09	10.39	5.09	7.86	13.37	2.60	12.11	3.95	8.10	16.49
2013	9.80	12.77	7.38	10.29	15.95	4.05	14.15	9.62	10.46	18.88
2018	9.58	15.20	6.92	10.97	14.25	4.45	13.05	9.30	9.56	17.09
Other Housing Units Share of All Housing Units										
2008	49.69	32.69	52.13	28.81	47.13	67.66	25.75	66.90	44.43	30.66
2013	45.83	32.42	51.57	31.26	46.27	61.93	32.28	45.86	44.77	30.70
2018	46.19	31.98	52.17	31.94	45.35	62.76	34.49	45.99	45.20	30.09

Panel B: Neighborhoods where Hispanics Are Underrepresented										
	All	Brevard	Broward	Duval	Lee	Miami-Dade	Orange	Palm Beach	Pinellas	Polk
Total Number of Housing Units (in thousands)										
2008	2391.52	151.48	463.70	192.80	158.16	352.21	231.33	406.29	293.56	141.97
2013	2466.00	154.86	465.79	203.58	162.54	361.31	264.98	407.06	298.94	146.94
2018	2575.36	156.17	476.40	213.17	175.82	375.34	293.75	426.10	304.60	154.00
Total Number of Single-Family Rentals (in thousands)										
2008	188.86	15.70	25.69	22.75	21.85	13.23	27.48	16.56	25.92	19.67
2013	268.37	19.32	37.70	29.89	26.04	20.59	36.68	41.43	33.19	23.55
2018	278.75	23.29	36.53	35.00	25.42	23.27	38.42	42.15	31.32	23.36
Total Number of Other Housing Units (in thousands)										
2008	1181.73	53.76	254.81	53.97	74.85	230.79	66.63	271.31	129.72	45.89
2013	1126.05	55.42	253.92	60.76	75.71	222.87	93.23	181.47	133.89	48.78
2018	1182.18	55.37	261.04	64.11	79.74	234.69	107.76	191.61	137.79	50.08
Single-Family Rentals Share of Single-Family Housing										
2008	15.61	16.06	12.30	16.39	26.23	10.89	16.69	12.27	15.82	20.47
2013	20.03	19.42	17.79	20.93	29.99	14.87	21.36	18.37	20.11	23.99
2018	20.01	23.10	16.96	23.48	26.46	16.54	20.66	17.97	18.78	22.48
Single-Family Rentals Share of All Housing Units										
2008	7.90	10.36	5.54	11.80	13.82	3.75	11.88	4.08	8.83	13.86
2013	10.88	12.47	8.09	14.68	16.02	5.70	13.84	10.18	11.10	16.02
2018	10.82	14.91	7.67	16.42	14.46	6.20	13.08	9.89	10.28	15.17
Other Housing Units Share of All Housing Units										
2008	49.41	35.49	54.95	27.99	47.32	65.53	28.80	66.78	44.19	32.32
2013	45.66	35.79	54.51	29.84	46.58	61.68	35.18	44.58	44.79	33.20
2018	45.90	35.45	54.79	30.07	45.35	62.53	36.69	44.97	45.24	32.52

Table 3
Dependent Variable: Percent Black of Block Group
Sample: Percent Black of Block Group < Percent Black of County

	All Block Groups	Block Groups by Neighborhood Income		
		Low	Middle	High
	(1)	(2)	(3)	(4)
% SF Rentals	0.537***	0.930***	0.464**	0.401
	(0.147)	(0.217)	(0.234)	(0.332)
	[1.009]	[1.591]	[0.939]	[0.742]
% Other Housing	0.093***	0.190***	0.094**	0.061
	(0.023)	(0.050)	(0.040)	(0.045)
	[0.611]	[0.914]	[0.598]	[0.463]
First-stage *F*	118	61	29	20
Block Groups	3,927	989	1,301	1,628
Observations	23,561	5,934	7,806	9,767

Notes: All regressions include nonresidential controls, block group fixed effects, and year fixed effects. Robust standard errors clustered at the block group level are in parentheses. The estimated effects from a within-neighborhood standard deviation change in the explanatory variable are in brackets. **, *** indicate significance at the 5 and 1 percent levels, respectively.

Table 4
Dependent Variable: Percent Hispanic of Block Group
Sample: Percent Hispanic of Block Group < Percent Hispanic of County

	All Block Groups	Block Groups by Neighborhood Income		
		Low	Middle	High
	(1)	(2)	(3)	(4)
% SF Rentals	−0.539***	−0.738***	0.071	−1.253
	(0.208)	(0.238)	(0.315)	(0.804)
	[−1.114]	[−1.540]	[0.152]	[−2.474]
% Other Housing	−0.103**	−0.173***	0.000	−0.217
	(0.041)	(0.066)	(0.058)	(0.141)
	[−0.654]	[−0.845]	[0.000]	[−1.457]
First-stage *F*	96	104	22	10
Block Groups	3,407	1,083	1,003	1,311
Observations	20,441	6,498	6,018	7,865

Notes: All regressions include nonresidential controls, block group fixed effects, and year fixed effects. Robust standard errors clustered at the block group level are in parentheses. The estimated effects from a within-neighborhood standard deviation change in the explanatory variable are in brackets. **, *** indicate significance at the 5 and 1 percent levels, respectively.

Table 5
Dependent Variable: Percent White of Block Group
Sample: Percent White of Block Group < Percent White of County

	All Block Groups	Block Groups by Neighborhood Income		
		Low	Middle	High
	(1)	(2)	(3)	(4)
% SF Rentals	−0.087	−0.135	−0.178	0.470
	(0.181)	(0.275)	(0.292)	(0.699)
	[−0.186]	[−0.275]	[−0.412]	[1.008]
% Other Housing	−0.012	−0.034	−0.014	0.049
	(0.033)	(0.084)	(0.053)	(0.069)
	[−0.071]	[−0.143]	[−0.093]	[0.483]
First-stage *F*	195	116	71	15
Block Groups	2,500	1,290	857	344
Observations	15,000	7,740	5,142	2,064

Notes: All regressions include nonresidential controls, block group fixed effects, and year fixed effects. Robust standard errors clustered at the block group level are in parentheses. The estimated effects from a within-neighborhood standard deviation change in the explanatory variable are in brackets.

Table 6
Results Based on Splitting Neighborhoods by Dominant Group

Dependent Variable	Percent Black		Percent White		Percent Hispanic	
Neighborhood Type	White	Hispanic	Black	Hispanic	Black	White
	(1)	(2)	(3)	(4)	(5)	(6)
% SF Rentals	0.552**	0.597***	0.031	−0.287	−1.036***	−0.218
	(0.256)	(0.187)	(0.314)	(0.291)	(0.300)	(0.315)
	[1.040]	[1.112]	[0.074]	[−0.558]	[−2.343]	[−0.436]
% Other Housing	0.110**	0.078***	0.017	−0.039	−0.268***	−0.029
	(0.047)	(0.023)	(0.083)	(0.042)	(0.077)	(0.059)
	[0.673]	[0.584]	[0.090]	[−0.269]	[−1.516]	[−0.193]
First-stage *F*	49	71	53	103	78	46
Block Groups	2,814	1,112	1,173	1,325	830	2,576
Observations	16,883	6,672	7,038	7,950	4,980	15,455

Notes: All regressions include nonresidential controls, block group fixed effects, and year fixed effects. Robust standard errors clustered at the block group level are in parentheses. The estimated effects from a within-neighborhood standard deviation change in the explanatory variable are in brackets. **, *** indicate significance at the 5 and 1 percent levels, respectively.

Table 7
Estimated Effects from Estimating Household Tenure Models

	Black (1)	Hispanic (2)	White (3)
All households	0.284**	−0.340**	−0.273
	(0.129)	(0.163)	(0.175)
	[0.534]	[−0.700]	[−0.584]
Renters	0.197**	−0.644***	0.002
	(0.097)	(0.135)	(0.114)
	[0.370]	[−1.325]	[0.004]
Owners	0.087	0.304**	−0.275*
	(0.080)	(0.134)	(0.145)
	[0.164]	[0.625]	[−0.588]
First-stage *F*	118	96	196
Block Groups	3,927	3,406	2,499
Observations	23,561	20,435	14,994

Notes: All regressions include nonresidential controls, block group fixed effects, and year fixed effects. Robust standard errors clustered at the block group level are in parentheses. The estimated effects from a within-neighborhood standard deviation change in the explanatory variable are in brackets. *, **, *** indicate significance at the 10, 5, and 1 percent levels, respectively.

Table 8
Estimated Effects from Estimating Migration Models
Informing the Percent Black Results

	All Block Groups	Block Groups by Neighborhood Income		
		Low	Middle	High
	(1)	(2)	(3)	(4)
Black Effect[1]	0.510***	0.796***	0.467	0.467
	(0.166)	(0.229)	(0.284)	(0.352)
Hispanic Effect	0.050	0.176**	−0.037	0.029
	(0.034)	(0.087)	(0.034)	(0.048)
White Effect	0.013	−0.015	0.039	0.041
	(0.025)	(0.037)	(0.035)	(0.069)

Notes: Black, Hispanic and White Effects are defined by equations (3), (4), and (5) in the text, respectively. All regressions include nonresidential controls, block group fixed effects, and year fixed effects. Robust standard errors clustered at the block group level are in parentheses. **, *** indicate significance at the 5 and 1 percent levels, respectively.

Table 9
Estimated Effects from Estimating Migration Models
Informing the Percent Hispanic Results

	All Block Groups	Block Groups by Neighborhood Income		
		Low	Middle	High
	(1)	(2)	(3)	(4)
Black Effect[1]	−0.052	−0.054	0.062	−0.432**
	(0.074)	(0.077)	(0.093)	(0.187)
Hispanic Effect	−0.300*	−0.521***	0.053	−0.068
	(0.178)	(0.200)	(0.295)	(0.623)
White Effect	−0.179**	−0.091	−0.055	−0.819
	(0.087)	(0.059)	(0.084)	(0.520)

Notes: Black, Hispanic and White Effects are defined by equations (3), (4), and (5) in the text, respectively. All regressions include nonresidential controls, block group fixed effects, and year fixed effects. Robust standard errors clustered at the block group level are in parentheses. *, **, *** indicate significance at the 10, 5, and 1 percent levels, respectively.

Table 10
Estimated Effects from Estimating Migration Models
Informing the Percent White Results

	All Block Groups	Block Groups by Neighborhood Income		
		Low	Middle	High
	(1)	(2)	(3)	(4)
Black Effect[1]	−0.103	−0.303***	−0.003	0.321
	(0.101)	(0.116)	(0.132)	(0.606)
Hispanic Effect	0.003	0.047	−0.041	0.079
	(0.086)	(0.120)	(0.169)	(0.292)
White Effect	−0.012	0.050	−0.139	0.159
	(0.126)	(0.205)	(0.217)	(0.292)

Notes: Black, Hispanic and White Effects are defined by equations (3), (4), and (5) in the text, respectively. All regressions include nonresidential controls, block group fixed effects, and year fixed effects. Robust standard errors clustered at the block group level are in parentheses. *** indicates significance at the 1 percent level.

Appendix Table A.1 Complete Set of 2SLS Estimates of Table 3 Model

Dependent Variable: Percent Black of Block Group Sample: Percent Black of Block Group < Percent Black of County				
	All Block Groups	Block Groups by Neighborhood Income		
		Low	Middle	High
	(1)	(2)	(3)	(4)
% SF Rentals	0.537***	0.930***	0.464**	0.401
	(0.147)	(0.217)	(0.234)	(0.332)
	[1.009]	[1.591]	[0.939]	[0.742]
% Other Housing	0.093***	0.190***	0.094**	0.061
	(0.023)	(0.050)	(0.040)	(0.045)
	[0.611]	[0.914]	[0.598]	[0.463]
Shopping Space	−1.560	−2.326	0.401	−2.217
	(1.575)	(3.335)	(1.451)	(2.157)
Other Commercial Space	−0.642	−1.020	−0.569	−0.684
	(0.579)	(1.980)	(0.610)	(0.943)
Industrial Space	0.189	6.624***	−3.338*	0.270
	(0.922)	(1.907)	(1.734)	(0.909)
Park Land	−0.038	−0.202	−0.545	−0.008
	(0.101)	(2.181)	(1.065)	(0.098)
Vacant Industrial Land	−3.557***	−7.628**	−1.354*	−8.886***
	(1.254)	(3.795)	(0.768)	(3.077)
Restaurants	0.284*	0.713*	0.180	0.057
	(0.148)	(0.369)	(0.197)	(0.237)
Alcohol Serving Places	0.028	0.830	−0.738*	0.217
	(0.214)	(0.657)	(0.445)	(0.246)
First-stage *F* Stat	118	61	29	20
Block Groups	3,927	989	1,301	1,628
Observations	23,561	5,934	7,806	9,767

Notes: All regressions include block group and year fixed effects. The nonresidential controls are the aggregated square footages (in millions) for shopping commercial properties, other commercial properties and industrial space, land areas (in square miles) of parks and vacant industrial land, the number of restaurants (excluding fast-food), and the number of alcohol serving establishments other than restaurants. Robust standard errors clustered at the block group level are in parentheses. The estimated effects from a within-neighborhood standard deviation change in the explanatory variable are in brackets. *, **, *** indicate significance at the 10, 5, and 1 percent levels, respectively.

Appendix Table A.2 Complete Set of 2SLS Estimates of Table 4 Model

Dependent Variable: Percent Hispanic of Block Group Sample: Percent Hispanic of Block Group < Percent Hispanic of County				
	All Block Groups	Block Groups by Neighborhood Income		
		Low	Middle	High
	(1)	(2)	(3)	(4)
% SF Rentals	−0.539***	−0.738***	0.071	−1.253
	(0.208)	(0.238)	(0.315)	(0.804)
	[−1.114]	[−1.540]	[0.152]	[−2.474]
% Other Housing	−0.103**	−0.173***	0.000	−0.217
	(0.041)	(0.066)	(0.058)	(0.141)
	[−0.654]	[−0.845]	[0.000]	[−1.457]
Shopping Space	0.584	3.346	2.044	−5.407
	(1.648)	(3.347)	(1.914)	(4.584)
Other Commercial Space	−1.703**	−1.499	−0.602	−3.041***
	(0.708)	(2.926)	(1.000)	(1.050)
Industrial Space	1.458	6.576*	7.504*	−1.909**
	(1.812)	(3.583)	(4.527)	(0.841)
Park Land	0.101	4.081***	−0.182*	0.181
	(0.100)	(1.562)	(0.103)	(0.130)
Vacant Industrial Land	0.881	8.249***	−2.442	2.495
	(0.672)	(2.563)	(1.559)	(2.595)
Restaurants	0.114	0.479	0.112	−0.186
	(0.212)	(0.394)	(0.389)	(0.316)
Alcohol Serving Places	0.080	−0.028	0.477	0.187
	(0.239)	(0.469)	(0.489)	(0.351)
First-stage *F* Stat	96	104	22	10
Block Groups	3,407	1,083	1,003	1,311
Observations	20,441	6,498	6,018	7,865

Notes: All regressions include block group and year fixed effects. Robust standard errors clustered at the block group level are in parentheses. The estimated effects from a within-neighborhood standard deviation change in the explanatory variable are in brackets. *, **, *** indicate significance at the 10, 5, and 1 percent levels, respectively. See the notes to Table A.1 for a description of the nonresidential controls.

Appendix Table A.3 Complete Set of 2SLS Estimates of Table 5 Model

	All Block Groups	Block Groups by Neighborhood Income		
Dependent Variable: Percent White of Block Group Sample: Percent White of Block Group < Percent White of County				
		Low	Middle	High
	(1)	(2)	(3)	(4)
% SF Rentals	−0.087	−0.135	−0.178	0.470
	(0.181)	(0.275)	(0.292)	(0.699)
	[−0.186]	[−0.275]	[−0.412]	[1.008]
% Other Housing	−0.012	−0.034	−0.014	0.049
	(0.033)	(0.084)	(0.053)	(0.069)
	[−0.071]	[−0.143]	[−0.093]	[0.483]
Shopping Space	0.198	−4.682	7.215	1.294
	(2.014)	(4.281)	(6.453)	(2.543)
Other Commercial Space	1.193	0.778	1.777	−3.780*
	(1.386)	(3.094)	(1.108)	(2.218)
Industrial Space	−0.826	−1.519	−1.658	−1.786
	(1.153)	(2.430)	(2.136)	(3.015)
Park Land	0.574	2.003	10.829	0.696***
	(0.485)	(6.235)	(14.311)	(0.252)
Vacant Industrial Land	1.073	7.994	9.927*	12.150
	(1.625)	(11.912)	(5.354)	(12.994)
Restaurants	0.297	0.753*	−0.536	−0.245
	(0.318)	(0.437)	(0.463)	(1.350)
Alcohol Serving Places	−1.001**	−1.113*	−1.590	0.779
	(0.494)	(0.633)	(0.967)	(1.610)
First-stage *F* Stat	195	116	71	15
Block Groups	2,500	1,290	857	344
Observations	15,000	7,740	5,142	2,064

Notes: All regressions include block group and year fixed effects. Robust standard errors clustered at the block group level are in parentheses. The estimated effects from a within-neighborhood standard deviation change in the explanatory variable are in brackets. *, **, *** indicate significance at the 10, 5, and 1 percent levels, respectively. See the notes to Table A.1 for a description of the nonresidential controls.

Appendix Table A.4 Complete Set of 2SLS Estimates of Table 6 Model
Results Based on Splitting Neighborhoods by Dominant Group

Dependent Variable	Percent Black		Percent White		Percent Hispanic	
Neighborhood Type	White	Hispanic	Black	Hispanic	Black	White
	(1)	(2)	(3)	(4)	(5)	(6)
% SF Rentals	0.552**	0.597***	0.031	−0.287	−1.036***	−0.218
	(0.256)	(0.187)	(0.314)	(0.291)	(0.300)	(0.315)
	[1.040]	[1.112]	[0.074]	[−0.558]	[−2.343]	[−0.436]
% Other Housing	0.110**	0.078***	0.017	−0.039	−0.268***	−0.029
	(0.047)	(0.023)	(0.083)	(0.042)	(0.077)	(0.059)
	[0.673]	[0.584]	[0.090]	[−0.269]	[−1.516]	[−0.193]
Shopping Space	−0.344	−1.159	1.978	−1.522	0.767	−2.329***
	(0.581)	(1.141)	(1.249)	(1.757)	(0.700)	(0.650)
Other Commercial Space	0.831	−2.271	0.491	−2.507	4.245	0.151
	(1.032)	(2.481)	(1.887)	(1.681)	(3.874)	(0.960)
Industrial Space	0.578	−0.592	−5.250	2.639	8.164*	0.009
	(1.731)	(0.866)	(5.696)	(1.825)	(4.649)	(1.886)
Park Land	−0.017	−12.211***	7.847	0.237	−7.526	0.094
	(0.101)	(2.829)	(10.331)	(0.201)	(10.007)	(0.100)
Vacant Industrial Land	−4.039***	−0.925	−0.188	12.028***	−14.092*	1.194***
	(1.288)	(1.577)	(0.422)	(3.885)	(7.712)	(0.345)
Restaurants	0.227	0.621	0.406	0.152	1.765**	−0.057
	(0.145)	(0.516)	(0.463)	(0.434)	(0.780)	(0.216)
Alcohol Serving Places	0.007	−0.045	−1.321**	−0.299	0.700	0.013
	(0.218)	(0.815)	(0.625)	(0.797)	(0.533)	(0.265)
First-stage *F* Stat	49	71	53	103	78	46
Block Groups	2,814	1,112	1,173	1,325	830	2,576
Observations	16,883	6,672	7,038	7,950	4,980	15,455

Notes: All regressions include block group and year fixed effects. Robust standard errors clustered at the block group level are in parentheses. The estimated effects from a within-neighborhood standard deviation change in the explanatory variable are in brackets. *, **, *** indicate significance at the 10, 5, and 1 percent levels, respectively. See the notes to Table A.1 for a description of the nonresidential controls.