Not In My Neighborhood: The Effects of Single-Family Rentals on Home Values[1]

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Abstract

Since the Great Recession single-family rentals have increased as a share of the housing units within America's neighborhoods. Homeowners are concerned that this shift in housing tenure will lower their neighborhood's quality and have an adverse effect on their property values. No current evidence exists on whether these concerns have any validity. In this paper, we utilize a six year balanced panel of neighborhoods from the state of Florida's metropolitan areas to study the impacts that single-family rentals have on the values of single-family homes. Our case for casualty is buttressed by estimating house value models that include time and neighborhood fixed effects, treat the rentals as endogenous variables, and control for sample selection. Our results show that share increases in single-family rentals lower house prices, but the effects vary between central cities and suburbs, across neighborhoods of different income levels and density, by the price of the rental unit, and whether the owner has a mailing address outside the state of Florida.

[1] We wish to thank the editor, Henry Pollakowski, and two anonymous referees for comments that substantially improved our paper.

1. Introduction

Within many of America's traditional single-family (SF) neighborhoods housing tenure has been shifting from owner-occupancy to rentals. Figures 1 and 2 show the upward climb in the total number of SF rentals and as a percentage of the SF housing stock and from 2005 to 2017 for the nation and the state of Florida, respectively.[2] At the national level, the rental percentage has climbed roughly 4 percentage points, from 13 to 17 percent. Particularly strong has been Florida's growth in rentals, with an increase of 7 percentage points, from 13 to 20 percent.[3] The impetus behind these shifts 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). The rise in SF rentals within their neighborhood has concerned many homeowners, who believe that their property values may be in jeopardy. These concerns have frequently been voiced in media reports (for example, Schmit 2012, Yoder 2012, Dewan 2013, and Fottrell 2013). In response, a growing number of local governments and Homeowners Associations are placing limits on the number of neighborhood single-family rentals (Yoder 2012) or devising other programs to reduce their number.[4] Constraints on the supply of SF rentals may reduce social welfare. Households preferring to rent may find it harder to find what they want in a tighter rental market and housing affordability may suffer within higher-quality neighborhoods, exacerbating racial and income segregation.[5] Hence, it is important to determine whether

[2] The figure also shows 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.
[3] Additional data documenting the growing importance of the SF rental market is provided by Freddie Mac (2019). Based on their analysis of American Community Survey data, they conclude 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 rental occupied households.
[4] An example is provided by Coulson and Wommer (2019) who report that homeowners' concerns caused State College, Pennsylvania, to establish a Homestead Investment program to buy homes and resell them only to owner-occupants, with a deed restriction that they could only be resold to other owner-occupants.
[5] Ihlanfeldt and Yang (2019) study the relationship between SF rentals and neighborhood racial segregation and find a larger share of rentals in neighborhoods where blacks have historically been underrepresented reduces segregation.

homeowner concerns surrounding the growth in SF rentals are grounded in reality. To our knowledge there is no current evidence on this issue.

We utilize a six-year balanced panel of neighborhoods from Florida's metropolitan areas to study the impacts that SF rentals have on the values of SF homes.[6] Changes in housing values for 2788 neighborhoods, yielding 16,728 neighborhood/year observations are measured over the years 2013 to 2018 using the Federal Housing Finance Agency's (FHFA) House Price Index (HPI) for census tracts. The natural log of the HPI is regressed on SF rentals as a percentage of the neighborhood's housing units, along with the percentage of other housing units. The percentage of SF owner-occupied homes serves as the excluded reference category. The estimated models control for sample selection, treat SF rentals as endogenous, and along with year and tract fixed effects include an extensive set of control variables describing the demographics and non-residential properties within the neighborhood. Due to the large size of our sample, we are able to investigate how the impact of SF rentals on neighborhood house values varies among different types of rentals and neighborhoods, where the latter are broken down by income level, location between central cities and suburbs, and housing unit density.

2. Why Might SF Rentals Reduce Single-Family Home Values?

There are a number of possible pathways that may cause SF rentals to lower neighborhood SF home values. First, a number of studies have found that rentals are less well maintained than owner-occupied housing (Galster 1983, Shilling, Sirmans and Dombrow 1991, Harding, Miceli and Sirmans 2000). Because renters enjoy only a consumption and not an investment return on

[6] A balanced data panel contains an observation of the same unit (in our case, the neighborhood) in every time period (year). Using a balanced panel has the advantages over unbalanced panel in that it reduces the noise introduced by unit heterogeneity and yields more reliable estimates especially when missing values in an unbalanced panel may result from nonrandom attrition.

their maintenance, they have less incentive to keep up the appearance of their home in comparison to homeowners, who benefit from both types of returns. Landlords do have an incentive to maintain the property, but only from an investment perspective. Coulson and Li (2013) also suggest that maintenance costs are higher if the landlord is an absentee one, which is usually the case. Under maintained housing units may emit negative sight externalities that take away from the attractiveness of the neighborhood and lower housing values.

A second possible pathway is that for a number of reasons rentals may increase neighborhood crime. First, criminals may expect that they will be less likely to be apprehended in a neighborhood with rentals. Two arguments can be made. First, "passive policing" within the neighborhood may decline. As coined by Goodstein and Lee (2010), passive policing refers to the efforts that neighborhood residents make to control crime within their own neighborhood. Having no claim to ownership, renters are less invested in the neighborhood than homeowners, who have strong financial incentives to maintain neighborhood quality. Therefore, renters are less likely to engage in passive policing, whether it takes the form of something informal, like providing more "eyes on the street," or something more formal, such as participating in neighborhood watch programs. Second, the perceived probability of apprehension within the neighborhood may also decline if rental housing lowers the general physical appearance of the neighborhood, as suggested above. According to "broken windows" theory (Kelling and Wilson, 1982), this decline in the appearance of the neighborhood may signal to criminals a lack of concern for the neighborhood on the part of its residents or an area that is not well-policed, resulting in a lower perceived risk of getting caught. Besides reducing criminals' assessment of capture, rentals may increase crime by changing the composition of neighborhood residents. Since renters have, on average, lower incomes than homeowners, they face lower opportunity costs when deciding whether to participate in criminal activities (Becker, 1968). Because a large number of studies have found that higher neighborhood crime results in lower housing values (Rizzo 1979, Naroff, Hellman and Skinner 1980, Burnell 1988, Gibbons 2004, Tita, Petras and Greenbaum 2006, Ihlanfeldt and Mayock 2010), an increase in SF rentals may reduce house values through the crime pathway.

Finally, in comparison to owner occupants, rental tenants are more transient, which may result in less commitment to improve the schools, parks, and other amenities of the neighborhood. In other words, renters, in comparison to homeowners, are less civically engaged. An absence of involvement may also result because without ownership renters have no financial stake in the quality of the neighborhood. Since it well known that the quality of schools (Black 1999, Crone 2006, Clapp, Nanda and Ross 2008) and other local amenities (Espey and Owusu-Edusei 2001) affect property values, renter disinterest may play a role in reducing house values.

3. Literature Review

Wang *et al.* (1991) provided the first evidence on the impact of SF rentals on the value of SF home values. Their sales transactions came from SF home subdivisions in San Antonio, Texas, covering the years 1984–1986. They measured proximity to SF rentals as the percentage of rentals among the closest five and eight SF homes. They found that if a house is surrounded by two rental properties out of the closest five houses or three rentals out of the closest eight houses the selling price would decrease by 2 percent, *ceteris paribus*.

Numerous hedonic SF price studies have included the neighborhood homeownership rate as an explanatory variable. Because the homeownership rate and the rental rate are inversely related, these studies seemingly are relevant to the present study. However, their poor methodological design suggests they should receive scant attention. Haurin, Dietz and Weinberg (2002), Coulson, Hwang and Imai (2002) and Coulson and Li (2013) critique these studies concluding that all of their results are suspect because none controlled for neighborhood sorting by households. Hence, the correlation found between the homeownership rate and house price, which is almost always positive, is likely to be spurious due to unobserved heterogeneity across neighborhoods.

Coulson and his colleagues completed two studies (Coulson, Hwang and Imai 2002, Coulson and Li 2013) that are the first to account for the sorting of households across neighborhoods in estimating the impact of the homeownership rate on the value of housing within the neighborhood. The empirical model in the first paper had a probit equation that modeled the choice of tenure and a hedonic housing expenditure equation that combined both rental and owner-occupied SF homes. Expenditures for the latter homes were obtained by taking 7.5 percent of the homeowner's estimate of value. To estimate their model, they used the cluster samples from the 1993 American Housing Survey (AHS). The clusters comprised the 10 to 11 closest SF homes surrounding the sampled SF home. Included in their hedonic model was the percentage of the surrounding units that were owner-occupied, which entered their model quadratically allowing for a non-linear effect. They found that changing one of the rental units within the cluster to owner-occupancy raises annual neighborhood expenditures by $341, on average. Their second paper also relied upon the AHS clusters but included two years of data (1989, 1993) on each sampled SF home. The panel nature of the data allowed for a more convincing identification strategy than that employed in their first paper. The homeowner's estimate of market value was regressed on the cluster's homeownership rate controlling for structural and neighborhood characteristics, as well as house and neighborhood fixed effects. Other models were also estimated that instrumented percent owner-occupied and other variables using lagged values. They found that a nine percent increase in the ownership rate of the cluster increases house value by 4.5 percent.

These studies limited their analysis to a very specific type of neighborhood where the only nearby homes were SF properties, some of which were rentals. Another limitation is that only rentals in very close proximity to the sample property were measured, while it may be the composition of the housing stock at the neighborhood level that also registers an effect. Also, at issue, is the age of the data used by these studies, with samples now being decades old. Finally, by addressing the possible endogeneity of SF rentals, the two papers by Coulson and his colleagues improve upon Wang *et al.*, but an advantage of the latter study is home values were measured with sales prices and not owner-estimates. Results may be unreliable if the value guesses of sampled homeowners incorrectly capture the contribution made to the neighborhood from more ownership and less renting.

4. Expected Differences in the Estimated Effects

An advantage of our large sample size of neighborhoods is that we can cut up the sample in various ways to answer a series of questions, regarding how the effects of SF rentals on neighborhood house values might vary by type and location. Reliably answering these questions will help tailor policies specifically to where they are needed to mitigate the negative spillover effects of SF rentals. One question is how the house value effects of an increase in the neighborhood share of housing units represented by SF rentals vary across neighborhoods of different income levels. In comparison to high income neighborhoods, low income neighborhoods have higher crime, less well maintained housing units, and a lower percentage of residents who are civically engaged (Levin-Waldman, 2013). Recall, these are the three pathways whereby SF rentals may have a negative impact on neighborhood house values. Hence, on the margin, within a low income neighborhood quality may be less impacted by a share increase in SF rentals, resulting in less, if any, impact on house values. In other words, within a low income neighborhood there may be little difference in the negative externalities emitted by a rental and an owner-occupied SF home. On the other hand, homeowner associations are more frequently found within higher income neighborhoods (Cheung and Meltzer, 2014). Their protective covenants may work to curtail any negative sight externalities emitted by SF rentals in the neighborhood. Also, the desire to protect property wealth, which is arguably greater in higher income neighborhoods, may cause the homeowners of these neighborhoods to more closely monitor tenant behaviors and report to law enforcement activities that may be detrimental to the neighborhood. Due to these countervailing influences, it is *a priori* unclear whether the house value impacts of SF rentals will be smaller or larger within high in comparison to low income neighborhoods. The answer requires an examination of the data. We therefore divide our sample of neighborhoods into low, middle, and high income and estimate separate models for each income group.

A second question is whether suburban neighborhoods, in comparison to central city neighborhoods, are impacted more by an increase in the share of SF rentals. In comparison to central city neighborhoods, the housing stocks of suburban neighborhoods are more uniform in appearance, with vintages, architecture, and tenure displaying less diversity. Hence, a SF rental may represent less of an outlier (i.e., a break in uniformity) within a central city neighborhood, mitigating its effect on housing values. Separate models are estimated for central city and suburban neighborhoods.

Negative externalities emitted by any offensive activity are expected to be stronger within denser areas, assuming that impacts are mitigated by longer distances. In neighborhoods where there are more housing units per land area, a greater loss in neighborhood quality may result from the negative spillover effects produced by a single additional SF rental. Hence, our third question is whether an increase in SF rentals as a share of a neighborhood's housing units has a larger effect on house values within denser neighborhoods. We estimate separate models for low, medium, and high density neighborhoods.

A fourth question is whether the effects of SF rentals on house values differ between local versus non-local investors. Although we offer no evidence, because proximity offers convenience, local landlords may serve as their own property manager and/or general contractor, and may personally oversee the decision to rent to any given tenant. In contrast, non-local landlords are less likely to have a personal relationship with their tenants and may find it costly to personally oversee the condition of the property, which suggests a greater use of a property management firm.[7] If a local/non-local owner division corresponds to the use of a professional property management firm, the role that owner location may have on the effect that an increase in the share of SF rentals has on neighborhood house values will depend on the whether professionally managed SF rental properties result in smaller spillover effects. Mills et al. (2019) note that technological developments that occurred in the 2000s, such as cloud computing, the widespread use of personal mobile devices, and mobile internet connectivity have allowed for scattered-site property renovation, maintenance, and management to occur in a much more flexible, efficient manner, suggesting that the scale economies that can be exploited by management companies may enable them to provide better services to SF rentals than investors who manage their own properties. Nevertheless, the latter owners are expected to have the advantage in choosing reliable tenants. Thus, it is unclear, *a priori,* how the effects of SF rentals on neighborhood house values might vary with the location of their owners. We estimate models where SF rentals are categorized based on the location of the owner.

Another question of interest is whether SF rentals owned by corporations have a different effect on neighborhood housing values in comparison to rentals owned by individuals. While both local

[7] While we could not find any data on the use of property managers by investors in single-family rentals, the articles listed below discuss the difficulties encountered by a non-local owner trying to manage the property without the assistance of a professional management company:
https://magazine.realtor/commercial/feature/article/2015/09/demystifying-long-distance-landlording
https://www.rentecdirect.com/blog/long-distance-landlord/
https://www.lawdepot.com/blog/10-tips-for-the-long-distance-landlord/.

and non-local owners may be corporations, according to our data non-local (i.e., out of state) SF rentals are more frequently corporate owned.[8] We estimate models where rentals are defined by both their type of ownership and whether the owner's address is inside or outside the state of Florida.

The final issue we address is whether the effect of SF rentals on neighborhood house values varies with the quality of the rental. More expensive homes will require higher rents and are therefore occupied by higher income tenants. According to the economic model of crime (Becker 1968), higher incomes raise the opportunity cost of committing crimes; hence, SF rentals occupied by higher income tenants are less of a threat to the safety of the neighborhood. In addition, more expensive SF rentals are less likely to be owned by landlords seeking to earn higher profit margins by failing to invest in maintenance and improvement (aka, slumlords). We estimate models dividing SF rentals into less and more expensive to study their different effects on neighborhood house values.

5. Data

The balanced panel that we use to estimate our house price models is constructed at the census tract level covering the years 2013–2018; however, as we describe below, to construct our instrumental variables we employ base year values going back five years before the beginning of the panel to 2008. The census tracts used to form our panel come from Florida's 43 urban counties, as defined by the 2010 Census of Population and Housing. For these counties, the FHFA reports a HPI for 2788 tracts, covering all six years of our panel. The HPI is a weighted, repeat-

[8] For the average neighborhood in our sample, 4.8 percent of the housing units are SF rentals with an out of state owner's address and 15.0 percent of these are corporate owned. SF rentals with an in state owner's address represent 11.5 of the housing units, with 10.8 percent owned by corporations.

sales price index, measuring the movement of SF house prices from year to year.[9] It is based on transactions involving conforming, conventional mortgages purchased or securitized by Fannie Mae or Freddie Mac. The FHFA HPI index is not reported for tracts where there are an insufficient number of repeat sales. This resulted in 1010 tracts (26 percent of the total number of tracts) being excluded from our panel. These tracts are largely agricultural or commercial in character.[10]

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 census tract level broken into 83 categories. From these counts we selected the following residential units: SF detached homes and other residential units. Also selected are counts of a dozen different types of commercial/industrial properties, which are listed in Appendix Table A.1. These are property types that may affect the attractiveness of the neighborhood and have their own impact on neighborhood house values that may be correlated with the share of SF rentals. Hence, they are included among our set of covariates as control variables.

What is most important for our study is a field within the tax rolls which 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

9 The FHFA HPI for larger geographic areas has been published for the past two decades, but only recently has the census tract version become available. The census tract version of the HPI is described in Bogin, Doerner and Larson (2019). The methodology used to construct the HPI is covered in Calhoun (1996).

10 In our April 4, 2020 email from William Doerner of the FHFA he stated "You're correct that the lack of index is a lack of repeat sales. Our exclusion criteria was extremely generous. Instead of counting a pair as one transactions, we decoupled them and then deduped. So if a house sold in 2002, 2008, and 2012 then we'd have only 2 paired transactions but we would count the 'half pairs' as being 3 unique transactions. It's a slight difference from doubling the paired transactions because we don't want to count a transaction twice. To have an index reported, we wanted to have 100 total historical observations (half pairs) to turn an index 'on' and then it must have 10 observations in any given year to not turn back 'off'".

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 over estimate of the number of SF rentals to the extent that homeowners are living in the home but fail to apply for the homestead exemption. To guard against this, our second condition 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 (assume, for example, the year is 2015). A unit can satisfy our two conditions anytime in the previous 12 months. If the conditions were met early in 2014, it is unlikely that the unit is vacant during 2015. If the conditions were met toward the end of 2014, the unit may not be rented for all 12 months of 2015, depending on the time it takes for the owner to find a tenant.[13] As is well known, 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 results in the vast majority of our SF rentals being occupied. We are not studying the impact of vacant homes on neighborhood house values.

Our housing typology consists of owner-occupied SF homes, SF rentals, and other housing units, which are largely units in multifamily properties (86 percent). For the average neighborhood in our sample, SF rentals represent 16.8 percent of the total number of housing units, SF owner-occupied homes are 50.0 percent and other housing units are 33.1 percent. In some specifications

[11] A homestead exemption decreases a property's taxable value by as much as $50,000.
[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.
[13] Renter's Warehouse is a company that manages a large number of SF rentals in Florida. They report an average of 17 days to find a tenant.

of the models SF rentals are broken down into less expensive (LE) and more expensive (ME). Less expensive (more expensive) units are defined for each year and have a Just Value less than (greater than) the annual median value of the county. Just Value is the county property appraiser's best estimate of what the home would sell for on January 1 of the tax roll year.[14] Other breakdowns of the SF rentals are by the address of the owner: within the same zip code as the property, outside the zip code but within the same county as the property, outside the county containing the property but within Florida, and outside the state of Florida. To identify SF rentals that are corporate owned we followed the approach of Mills et al. (2019). SF rentals whose owner name includes the abbreviations "INC", "LP", or "LLC" are treated as corporate owned.

Neighborhoods are divided into City and Suburbs, based on the U.S. Census Bureau's identification of the Principal Cities of each metropolitan area. These are in the names given to each MSA.[15] If a neighborhood is within a Principal City it is considered a City neighborhood, otherwise it is a Suburban neighborhood. To categorize neighborhoods into low, middle, and high income categories we used median household incomes at the census tract level provided by the 2017 American Community Survey (ACS) 5-Year Estimates.[16] The latter estimates were also used to stratify our neighborhoods into low, medium, and high density, where density is defined as the number of housing units per square mile. The ACS 5-Year Estimates for the years 2013 to 2018 were used to obtain our neighborhood demographic controls. Households were categorized based on the race of the household head (black and white) and annual income. These variables are defined in the appendix.

[14] These Just Value estimates, which are used in the administration of the property tax, are based on standard assessment methods (*i.e.*, comparable sales, replacement cost, and the income approach) and are validated each year by the Florida Department of Revenue.

[15] For example, the Miami-Ft. Lauderdale-West Palm Beach MSA has three principal cities.

[16] Low, middle and high income are less than $45,000, between $45,000 and $60,000, and greater than $60,000, respectively.

In isolation, a SF rental may produce negative spillover effects that lower only nearby property values. Measuring the change in housing values at the tract level may be too large of an area to register the effect. However, our interest is how an increase in the share of a neighborhoods housing units represented by SF rentals impacts housing values. Our concern, therefore, is not with the impact area of a single SF rental but whether the rentals are concentrated in only a portion of the census tract. To study this issue, we investigated the distribution of SF rentals across the block groups that make up the tract by computing a GINI Coefficient for each tract. The median (mean) Gini Coefficient for all of our tracts equal .13 (.15), with 75% of the tracts having a Gini Coefficient of less than .25 . These results suggest that the rentals are distributed fairly evenly over the area covered by the average census tract.

6. Empirical Methodology

Our house price equation relates the natural log of the census tract HPI to the neighborhood shares of SF rentals and housing units other than SF homes, along with year and neighborhood fixed effects. Formally,

$$\ln HPI_{it} = \boldsymbol{s}_{it}'\boldsymbol{\beta} + \boldsymbol{x}_{it}'\boldsymbol{\theta} + \alpha_i + \eta_t + \varepsilon_{it}, \tag{1}$$

for $i = 1,2, \ldots, N$ and $t = 1,2, \ldots T$, where HPI_{it} is the House Price Index of tract i in year t, $\boldsymbol{s}_{it}$ is a vector of shares of housing units as percentages of the total number of housing units in tract i, $\boldsymbol{x}_{it}$ is a vector of control variables, α_i is the unobserved tract-specific effect, η_t is the year fixed effect, and ε_{it} is an idiosyncratic error. The share of SF owner-occupied properties is the excluded house type, which serves as our reference category. In our most basic model, the housing shares, $\boldsymbol{s}_{it}$, are the share of SF rentals, regardless of type, and the share of housing units other than SF homes (OHUs). In other specifications, as noted in Section 4, the SF rental shares are broken down into various types. Specifically, by the location of the owner: within the same zip code as the property, outside the same zip code but within the same county, outside the county but within the state, and outside the state; by more and less expensive; and by type of ownership: corporate and individually owned. The control variables include the neighborhood demographic variables and the non-residential property types.

In order to obtain a consistent estimate of $\boldsymbol{\beta}$ in (1), we have to carefully address two potential econometric problems—endogeneity and sample selection. First, although (1) includes tract fixed effects to control for unobservable time-invariant heterogeneity affecting the HPI, there may be time-varying unobservables that are correlated with SF rentals that have their own impact on neighborhood house values. Hence, to control for this possibility, there is a need for instrumental variables (IV) for the SF housing types that satisfy strict exogeneity (*i.e.*, variables that would be correlated with the housing shares that would not have their own influence on the HPI). Conceptually, it is reasonable to argue that a change in the neighborhood share of SF rentals is driven by factors both within the neighborhood and county-wide. While factors within the neighborhood may be endogenous to the HPI, county-wide factors should not be affected by conditions within the home neighborhood, especially if the county-wide factors are defined over the portion of the county that excludes the home census tract. Based on this logic, the following IV is suggested: first define a base year preceding the beginning of the panel. Using the entire county, then calculate the percentage change in the share of SF rentals at the county level between the base and current years, excluding the home neighborhood value. These percentage changes are then multiplied by a base year value of the SF rentals share to obtain a prediction ($\hat{s}_{it}$), assuming the growth in the share at the neighborhood level followed the change that occurred at the county level. Formally,

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

where i indexes the census tract, t indexes the current year, j indexes housing type, b is the base year, and c represents the county (excluding tract i). Note that by construction the IV varies over time, across counties and across neighborhoods within the same county. While HPI may affect $s_{it,j}$, it should not have an effect on $\hat{s}_{it,j}$. However, the validity of $\hat{s}_{it,j}$ 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 dampens the HPI. In that case, the instrument would, in part, be capturing 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 HPI. We used 2008 as our base year. While it is still possible that events 5 years prior to the beginning of the panel (2013) could affect the current HPI, this seems unlikely.[17]

The second problem that may result in inconsistent estimation of (1) is non-random sampling. As noted in Section 5, the FHFA HPI index is not reported for tracts that have an insufficient number of repeat sales. Therefore, the standard fixed effects two-stage least squares estimates may be

[17] The validity of our instrumental variable depends on satisfying two conditions—the instrument is strictly exogenous and not "weakly" correlated with the tested regressor. Supporting evidence on the exogeneity of our instrument is provided as one of our robustness checks. To detect weak instruments, we conduct the *F* test of the joint significance of the instruments in the first-stage reduced form regression in the models where SF rentals is the only variable requiring instrumentation (*i.e.*, SF rentals are not broken into different types). We follow Staiger and Stock's (1997) rule of thumb and reject the null hypothesis that our instrument is weak if the *F* value is 10 or larger. For models with multiple endogenous variables, Baum, Schaffer and Stillman (2003) have illustrated that the standard *F* statistic may not be sufficiently informative. A more informative test may be the Sanderson-Windmeijer (SW) (2016) conditional *F* statistic that tests the weak identification of individual endogenous regressors. Again, we use a SW *F* value of 10 or greater to reject that our instrument is weak. The standard *F* statistics are larger than 10 in 46 of the 49 reported cases, with the three exceptions still indicating a non-trivial correlation between the instrument and the endogenous variable. Hence, these results suggest that our results are not being biased by weak instruments. While the vast majority of the conditional *F* statistics are also larger than 10, in some cases they conflict with the information provided by the standard *F* statistic. Detailed test results are given in Appendix Tables A.5 and A.6.

subject to sample selection bias. To formally address this issue, we consider the following sample selection process:

$$d_{it} = 1[d_{it}^* > 0], \quad \text{where} \quad d_{it}^* = \mathbf{z}_{it}' \boldsymbol{\delta}_t + \mu_i + \gamma_t + v_{it}, \tag{3}$$

for $t = 1,2, \ldots T$, where $1[\cdot]$ is the indicator function, d_{it} is a selection indicator that equals one if HPI_{it} is observed ($d_{it}^* > 0$), and zero otherwise. d_{it}^* is a latent (unobserved) variable representing the propensity for a tract to have available HPI data; d_{it}^* is assumed to follow a linear process where $\mathbf{z}_{it}$ is a vector of exogenous variables that affects selection, μ_i is an unobserved heterogeneity, γ_t is the year fixed effect and v_{it} is an idiosyncratic error. Note that the parameters in $\boldsymbol{\delta}_t$ are allowed to be time-varying. This specification follows the model considered in Semykina and Wooldridge (2010), who showed that, under fairly general assumptions, consistent estimates of $\boldsymbol{\beta}$ in (1) in the presence of both endogeneity and sample selection can be achieved by a two-step procedure: In the first step, for each t, estimate the selection equation (3) by probit, where the unobserved heterogeneity is approximated by the Mundlak's (1978) device, and use the resulting estimates to obtain the inverse Mills ratio, denoted by $\hat{\lambda}_{it}$. In the second step, apply a pooled two-stage least squares (2SLS) estimation of the equation:

$$\ln HPI_{it} = \mathbf{s}_{it}' \boldsymbol{\beta} + \mathbf{x}_{it}' \boldsymbol{\theta} + \bar{\mathbf{z}}_i' \boldsymbol{\xi} + \rho_t \hat{\lambda}_{it} + \eta_t + e_{it}, \tag{4}$$

where $\bar{\mathbf{z}}_i$ is the within-tract time mean of the exogeneous regressors $\mathbf{z}_{it}$. The standard errors that are adjusted for the first-step estimation and robust to heteroskedasticity and serial correlation in $\{\varepsilon_{it}\}$ can be computed by the analytical formulae provided by Semykina and Wooldridge (2010).[18] The test for selection bias can be easily obtained by a Wald test of $H_0: \rho_1 = \rho_2 = \cdots = \rho_T = 0$. A rejection of the null hypothesis would indicate evidence of sample selection bias.

[18] The Stata code that implements the two-step estimation procedure is available at the website of Anastasia Semykina: http://myweb.fsu.edu/asemykina/.

The only remaining issue is the specification of $\boldsymbol{z}_{it}$. As emphasized in Semykina and Wooldridge (2010), "the procedure is convincing only if we have at least one IV for each endogenous element of $[\boldsymbol{s}_{it}]$ and then another exogenous variable that affects selection." Accordingly, we choose $\boldsymbol{z}_{it}$ to be the vector of all exogenous variables, including the log of the number of SF homes, denoted by $\ln m_{it}$, which is excluded from the reduced form regressions of the 2SLS. To put it another way, $\ln m_{it}$ provides another source of exogeneous variation for the house price equation in addition to the instruments $\hat{\boldsymbol{s}}_{it}$. Note that the observability of HPI_{it} is highly correlated with $\ln m_{it}$, since the larger stock of SF homes in a tract, the higher probability of enough repeat sales taking place in the tract for FHFA to report their house value index; however, HPI_{it} is unlikely to be affected by $\ln m_{it}$. Assuming $\boldsymbol{x}_{it}$ is strictly exogenous (conditional on α_i), the vector $\boldsymbol{z}_{it}$ consists of all variables in $\boldsymbol{x}_{it}$, the instruments $\hat{\boldsymbol{s}}_{it}$, and $\ln m_{it}$. The selection bias-corrected equation (4) is used for all of the models we estimate.

7. Descriptive Statistics

Table 1 shows the census tract mean percentage changes in the HPI and their standard deviations for each year of our panel. Housing prices increased monotonically over the six-year period, which mirrors the trend at the national level in the post-recession recovery period. However, the annual average appreciation rate for our sample of census tracts (9.3%) exceeded what occurred at the national level (5.7%), based upon the national FHFA HPI.

SF rentals as a share of a neighborhood's housing units are reported in Table 2. Mean values are broken down by both our SF rental and neighborhood typologies. Lumping all SF rentals together shows little variation in the share across the neighborhood types, ranging from 15 to 18 percent. Not unexpected is that the high income neighborhoods have the lowest percentage of SF rentals and the highest percentage of more expensive SF rentals, with the share in the highest income group roughly twice as large as within the lowest income group. Shares are similar between the central city and the suburbs. Regardless of the type of neighborhood, the breakdown by the location of the owner of the SF rentals reveals a fairly even distribution across the four defined locations.

Overall, our panel shows a good number of tracts within each neighborhood group (shown at the bottom of the table) ranging between 900 to 1888, and share totals for each of our SF rental types. Hence, our balanced panel is ideal for answering our questions of interest.

8. Results

The first issue we addressed is whether the housing shares could be treated as exogenous. The neighborhood shares entering our models are SF rentals (with and without the divisions into different types) and other housing units (OHUs). The share of OHUs is comprised almost entirely of units within multifamily properties. An annual increase in these units comes mostly from new construction. The length of time between the decision to build and occupancy is generally 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 many times involved), and demolition/construction all together commonly take years in the making. Hence, we do not expect the current HPI or time-varying within tract unobservables would impact the current share of OHUs. Furthermore, the decision to build is expected to be based on projections of future apartment rents and condominium prices and not on the projection of the future prices of SF homes. Hence, we treat the share of OHUs as exogenous in estimating our models.

Regarding the exogeneity of SF rentals, 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. Hence, in all of our regression we treated the share of SF rentals as endogenous.

The results from estimating our neighborhood HPI models are divided between Tables 3 and 4.[19] Table 3 reports the results from estimating equation (4) treating all SF rentals as the same (Panel A), dividing SF rentals into less and more expensive (Panel B), and breaking SF rentals down into the four locations describing the address of the property owner (Panel C). In each panel results are reported for all census tracts, census tracts within central cities, census tracts within the suburbs, and for low, middle, and high income census tracts. Table 4 reports results using a different neighborhood typology than used in Table 3, with neighborhoods divided into low, medium, and high density (Panel A). Panel B of Table 3 shows the results from dividing SF rentals based upon the owner's state location and type of ownership.

In the tables two numbers are reported for each explanatory variable. The first number is the estimated coefficient. Based upon our log-linear functional form, the estimated coefficient is interpreted as the percentage change in the HPI caused by a one percentage point increase in the neighborhood share of the housing type. The second number is the standard error clustered at the census tract level and corrected for the first-step estimation of the selection equation. It should be noted that the standard errors are robust to unknown heteroskedasticity and serial correlation of arbitrary forms. [20]

[19] Reported in the tables are the results obtained for the housing shares. Full results, including those for the control variables, are reported in the appendix.

[20] The results of the first-step probit estimations are not presented in order to save space and are available upon request. The log of number of SF homes is found to be positive and highly statistically significant in the first-step regressions, as expected. For each model we conducted a Wald test for selection bias. More

Panel A of Table 3 shows that an increase in the neighborhood share of SF rentals is associated with a reduction in neighborhood house values. For the sample of all census tracts, a one percentage point increase in the SF share reduces house values by 1.9 percent. The effect is statistically significant at the one percent level. The percentage reduction within Cities (1.0%) is about half as large as that within suburbs (1.9%), with both effects significant at the 5 percent level. Hence, the results are consistent with the hypothesis that the more varied mix of the residential units within central city in comparison to suburban neighborhoods mitigates the negative effect of the impact of SF rentals on house values. The estimations for the three neighborhood income groups yield percentage reductions in HPI equaling 3.0, 1.2 and 1.4 for low, middle, and high income neighborhoods, respectively. These results suggest that SF rentals have a stronger negative impact on house values within low in comparison to middle and high income neighborhoods. To assess the reasonableness of the estimates in Panel A, consider that the average census tract contains 2148 housing units (the sum of SF rentals, SF owner-occupied units and the individual units in OHUs); hence, a one percent share increase equals 22 additional SF rentals. In light of this number, the percentage reductions presented in the panel seem plausible in magnitude.

In Panel B, SF rentals are divided into less (LE) and more (ME) expensive units. While there is little difference in the estimates obtained for the full sample of neighborhoods, differences emerge for the various neighborhood types. For city, low income, and middle income neighborhoods an increase in the share of less expensive rentals is negative and significant, while an increase in the share of ME rentals is not significant. For high income neighborhoods, shares of both less expensive and more expensive rentals are insignificant. Standing in contrast to these results is

precisely, we tested for joint significance of the inverse Mills ratios while allowing for heteroskedasticity and serial correlation in the errors. The test statistic and associated *p*-value are given in the appendix. The test outcomes suggest that the null hypothesis of no selection bias is strongly rejected in all estimated models, and hence correcting for selection bias is warranted.

that within suburbs, while both LE and ME rentals significantly reduce neighborhood house values, the effect of more expensive rentals is roughly twice as large than that of less expensive rentals. Overall, the evidence supports the hypothesis that an increase in a neighborhood's share of housing units represented by less expensive SF rentals results in a greater reduction in neighborhood housing values than an equivalent increase in the share of more expensive SF rentals.

Panel C shows the results obtained from breaking SF rentals into the four alternative locations of the owner of the property: within the zip code of the rental, outside the zip code but within the county of the rental, outside the county but within Florida, and outside the state of Florida. There is a common pattern in the results for all neighborhoods and the neighborhood types. Across the three in state locations there is little difference in the results. For example, for all neighborhoods the estimated percentage reductions in HPI equal 3.4, 3.5, and 3.6 from a percentage point increase in the share of SF rentals owned within the same zip code as the rental, outside the zip code but within the same county, and outside the county but within the state, respectively. In contrast, SF rentals with an owner address out of the state have a much smaller effect on neighborhood house values that is generally not significant. The one exception is for high income neighborhoods where the only rentals having a negative effect on neighborhood property values or those with addresses outside the state. Because we have no data on rentals that are professionally managed, we cannot conclude that the contrasting in-state versus out-of-state results reflect possible efficiencies provided by these companies; however, we view this as a strong possibility that merits additional research.

Panel A of Table 4 uses a different neighborhood typology than used in Table 3. Neighborhoods are first ordered by the number of housing units per square mile and the distribution is divided into terciles with the first, second, and third groups defined as low, medium, and high density neighborhoods, respectively. The higher the density the greater the negative impact of a share increase in SF rentals on neighborhood house values. A one percentage point share increase in SF rentals reduces neighborhood house values by 1, 2, and 3 percent for low, medium, and high density neighborhoods, respectively. Because the results obtained with the location of the owner reported in Table 3 showed that the location difference that matters is whether the owner's address is within or outside the state of Florida, in Panel B of Table 4 we separate SF rentals into four categories based on the latter two locations and whether the rental is owned individually or by a corporation. The results show that it makes no difference whether the SF rentals whose owners' addresses are located out of state are owned by individuals or corporations. In both cases, the results parallel those reported in Table 3 showing that these rentals have little effect on neighborhood house values. For rentals whose owners are located within the state and are not a corporate entity, a one percentage point increase in their share is found to produce a highly significant 3.4 percent reduction in neighborhood house values. For these rentals that are owned by corporations the effect is not significant (the estimated coefficient is smaller than the estimated standard error). Again, a possible difference in the use of property management companies between rentals owned by individuals and corporations may play a role in accounting for these results.

All of the estimated models include the demographic variables and the non-residential property types as controls. The results with these variables are reported in the appendix. Increasing the percentage of the neighborhood's households falling into each of the race/income groups resulting in a decrease in the percentage of high income white households (the reference group) reduces neighborhood house values, with the black income groups tending to produce a somewhat larger decline than the corresponding white income groups. The effects of the non-residential properties on neighborhood house values vary across the neighborhood types, but consistent negative effects are found for department stores, recreation centers, and churches, while positive effects are found for service stations. Possible explanations for these findings are that the negative effects are associated with automobile congestion, while the positive effect is due to the neighborhood store that is usually part of a gas/petrol station, where customers can purchase goods conveniently while filling their vehicle with fuel.

9. 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 the results reported in Tables 3 and 4 are being driven by one or more of Florida's large counties, which because of their size have a disproportionately large number of neighborhoods as part of the state sample. The five largest counties are Miami-Dade, Broward, Palm Beach, Hillsborough, and Orange. Dropping these counties one at a time or all together has no discernable impact on the results.

We also 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. The estimated effects of the SF rental shares are smaller, but generally remain statistically significant, albeit at lower levels of significance. We also reconstructed our instrumental variable, retaining the home neighborhood value in computing the changes at the county level. This had almost no effect on the results reported in Tables.

Next, we were interested in further assessing the exogeneity of our instrumental variable by choosing a base year farther back than five years. Going back before 2008 reduced our accuracy in placing properties in the proper census tract. However, the time gap between the base year and the first year of our sample can be expanded by delaying the first year of our panel. If we start the panel with the year 2014 instead of 2013, the panel becomes a five-year panel instead of a six-year panel. The time gap between the base year of 2008 and 2014 is extended from 5 to 6 years. Similarly, if we start the panel with the year 2015 (2016), the panel is four (three) years in length and the base year is then 7 (8) years before the start of the panel. Using these various panels, we estimated the same model for Panel A of Table 3, but without the control variables.[21] The six, five, four, and three year panels yielded estimated coefficients for the share of SF rentals that ranged between -.011 and -.013, and all estimates are statically significant at the one percent level. These results lend support to our assumption that the base year share values are exogenous to the current year HPI values used to estimate our models.

Finally, we estimated all of our models without the neighborhood demographic variables and the non-residential property types. Our main conclusions on the effects of SF rentals on neighborhood house values continue to hold after dropping these variables.

10. Loss of Property Tax Revenue

Besides SF homeowners, another group for which our results have important consequences are local governments. By lowering the values of neighborhood homes, the negative spillover effects from SF rentals reduces the property tax revenues received by local governments. To obtain a rough estimate of the magnitude of the average tax loss per neighborhood, consider what would result from a one standard deviation increase in the share of SF rentals within the median neighborhood in our sample. With panel data, a standard deviation (SD) change can be measured as either "between" or "within" the observational units. The between SD comparison can be thought of as selecting two neighborhoods from the same year, with one experiencing and the

[21] The control variables become largely insignificant when reducing the length of panel due to limited intertemporal variation.

other not experiencing a standard deviation increase in the share of SF rentals. The within SD compares two years for the same neighborhood, where in one of the years but not the other there is a standard deviation increase in the share of SF rentals. Because the within SD change is a better gauge of the tax loss experienced by the median neighborhood, we employ this number. A within SD increase is 1.78 percent; hence, when multiplied by the estimated coefficient on the share of SF rentals (-.019) the house value percentage loss is 3.4 percent. According to Zillow, the median value of SF homes in Florida in 2015 equaled $160,000, so the loss in dollars would be $5440. Since the median neighborhood in 2015 contains 1438 SF homes, the total loss in value for the entire neighborhood is 7.8 million dollars. Florida's effective property tax is in the range of roughly 1.5 percent, which implies that a within one SD increase in the share of SF rentals would reduce tax revenue by $117,000. One important policy implication from the size of this tax loss is that strategies to mitigate the negative spillover effects from SF rentals could possibly be financed, at least in part, by local government tax increment financing, which dedicates tax increments within a certain defined district to finance the debt that is issued to pay for the project.

11. Conclusions

SF rentals have grown in importance as a component of the housing stocks of urban neighborhoods. This trend is likely to continue as there exists a strong demand for this type housing (Freddie Mac 2019). Homeowners have shown concerns that the increase in SF rentals could have an adverse effect on their property values and in some cases have made efforts to restrict the presence of these rentals within their neighborhoods. This paper has provided some new evidence suggesting that these concerns have some validity. Our estimated models show that a one percentage point increase in the SF rental share of a neighborhood's housing units can reduce house values by as much as 8 percent, depending on the type of rental and neighborhood. Most of our estimates, however, fall within a range of 2 to 5 percent. Our results are based on estimated models using a balanced panel that control for unobserved heterogeneity across and within tracts, sample selection resulting from the HPI not being reported for all census tracts, and the endogeneity of the rentals.

The large size of our panel allowed us to investigate differences in the house value effects of SF rentals among different types of neighborhoods and different types of rentals. We found that the negative impact of SF rentals on neighborhood house values is larger within suburbs than central cities, greater in low income than high income neighborhoods, larger in neighborhoods with a higher density of housing units, worse for less expensive than more expensive homes, and unimportant for properties that are owned by corporations or whose owners have addresses outside the state of Florida.

From a policy perspective a number of recommendations can be drawn from our results. Government intervention is suggested where market failure is evident and our detection of negative spillover effects from SF rentals suggests that this is the case. Moreover, our results suggest that the SF rental spillover phenomenon is worsening the housing wealth gap between low and high income homeowners. The rentals reduce home values more in low in comparison to high income neighborhoods. Hence, government intervention is justified, but a blanket approach is ill-advised. Because spillover effects vary by type of rental and the location of the rental, polices should be contextual in nature. We do not recommend limitations on the number or share of SF rentals. They offer a relatively new rental option in many neighborhoods that better meet the needs of many households. Moreover, there presence in high income neighborhoods increases housing affordability that has been found to increase racial integration (Ihlanfeldt and Yang 2019). Future research should be directed toward an understanding of the possible pathways whereby these particular rentals negatively impact neighborhood house values. With this knowledge the negative spillovers from the rentals hopefully can be mitigated.

The standard caveats regarding a study of our nature apply. Ours is the first study that uses recent data on the growth of SF rentals to analyze their spillover effects. Research is needed to determine if our results generalize to other states. However, the fact that we find rather consistent effects using neighborhoods throughout the metropolitan areas of Florida and find that these results are robust to dropping its largest counties suggest that our conclusions will be reproducible for other states.

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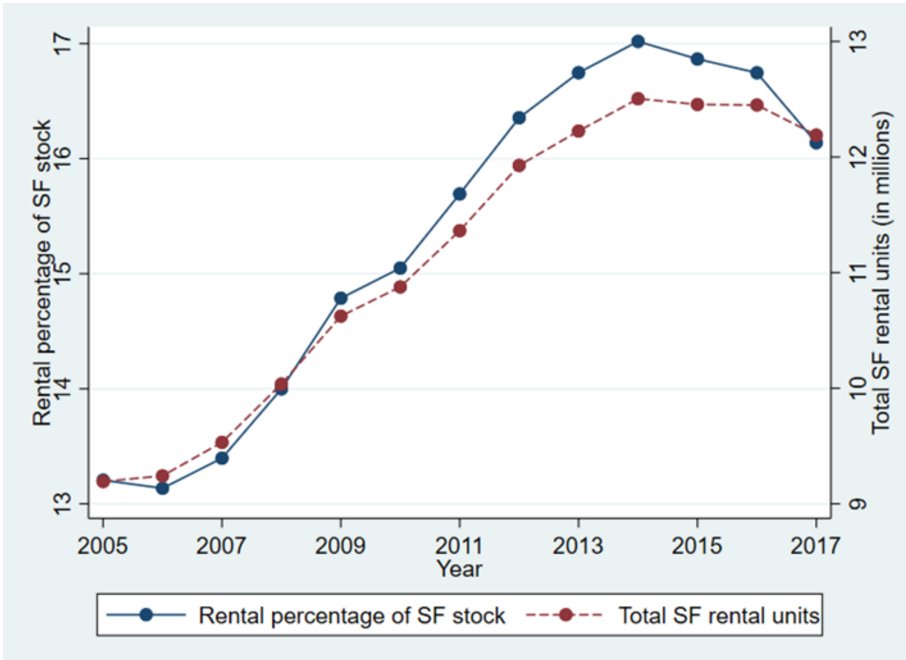
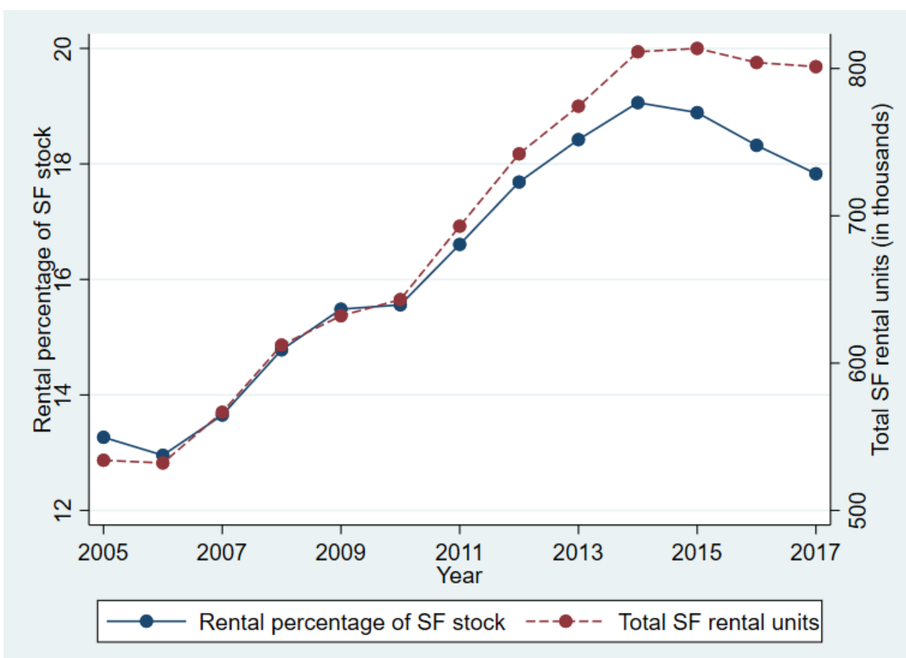
Figure 1 Rental percentage of SF stock and total SF rental units for the U.S.



Note: 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.



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

Table 1 FHFA House Price Index (HPI): Means and standard deviations (SD) of annual percentages changes in house values within census tracts.

	Percentage Change in HPI	
	Mean	SD
2013—2014	11.1	9.5
2014—2015	9.5	9.1
2015—2016	10.3	9.3
2016—2017	10.1	9.5
2017—2018	9.3	9.0

Table 2 Single-family rentals as a share of neighborhood housing units: Means and standard deviations.

	All Neigh	City	Suburbs	Income		
				Low	Middle	High
Total	16.83	17.85	16.34	18.10	17.69	14.88
	(8.84)	(8.74)	(8.86)	(10.09)	(8.97)	(6.96)
LE	9.23	10.0	8.83	13.94	10.11	4.11
	(8.90)	(8.96)	(8.84)	(10.10)	(7.93)	(5.09)
ME	7.60	7.81	7.50	4.15	7.58	10.77
	(5.99)	(5.88)	(6.04)	(4.01)	(5.92)	(5.77)
Owner location						
Zip code	4.06	4.35	3.92	4.39	4.11	3.70
	(3.21)	(3.04)	(3.28)	(3.51)	(3.24)	(2.85)
County	4.91	6.04	4.35	6.18	4.93	3.72
	(3.61)	(4.02)	(3.26)	(4.46)	(3.31)	(2.42)
State	3.02	2.69	3.18	3.42	3.12	2.56
	(2.34)	(2.03)	(2.54)	(2.67)	(2.59)	(1.81)
Out of state	4.85	4.77	4.89	4.12	5.53	4.91
	(4.39)	(4.34)	(4.41)	(3.45)	(5.11)	(4.34)
# of neighborhoods	2788	900	1888	915	885	985

Note: Neighborhoods are defined as census tracts. LE and ME are the shares of less and more expensive SF rentals, respectively. Owner location gives a breakdown of the shares of SF rentals by the location of the property owner: within the zip code of the rental, outside the zip code but within the county of the rental, outside the county but within the state of the rental, and outside of the state. Standard deviations are in parentheses.

Table 3 Results from estimating HPI models for the first set of sample divisions.

	All Neigh	City	Suburbs	Income		
				Low	Middle	High
			Panel A			
SF rentals	-0.01899***	-0.01095**	-0.01934***	-0.03030***	-0.01223***	-0.01401**
	(0.00397)	(0.00602)	(0.00494)	(0.00865)	(0.00467)	(0.00599)
OHUs	-0.00271**	-0.00306**	-0.00167	-0.00638**	-0.00465**	0.00064
	(0.00120)	(0.00166)	(0.00162)	(0.00265)	(0.00200)	(0.00129)
			Panel B			
SF rentals						
LE	-0.01940***	-0.02141**	-0.01394*	-0.02461**	-0.01077*	-0.01558
	(0.00639)	(0.00918)	(0.00742)	(0.01064)	(0.00634)	(0.02458)
ME	-0.02385**	0.00605	-0.03671***	-0.04007	-0.01417	-0.01920
	(0.01060)	(0.01849)	(0.01384)	(0.03352)	(0.01423)	(0.01977)
OHUs	-0.00288**	-0.00370**	-0.00205	-0.00527**	-0.00472**	0.00070
	(0.00128)	(0.00181)	(0.00195)	(0.00243)	(0.00224)	(0.00141)
			Panel C			
SF rentals						
Zip	-0.03404***	-0.02353**	-0.04335**	-0.08597**	-0.05687***	0.02221
code	(0.01048)	(0.00964)	(0.01881)	(0.03430)	(0.01651)	(0.01920)
County	-0.03478***	-0.02272	-0.04189**	-0.08616***	-0.04247***	0.02117
	(0.00946)	(0.01814)	(0.01713)	(0.03117)	(0.01371)	(0.02107)
State	-0.03624***	-0.02253**	-0.05012***	-0.08468*	-0.04739***	0.01224
	(0.00949)	(0.00965)	(0.01762)	(0.04516)	(0.01386)	(0.01862)
Out of	0.00223	-0.01608	0.00858	-0.03115	-0.01815**	0.04389**
state	(0.00762)	(0.01739)	(0.00954)	(0.02064)	(0.00870)	(0.01982)
OHUs	-0.00406**	-0.00531**	-0.00366	-0.01743**	-0.00961***	0.00226
	(0.00177)	(0.00217)	(0.00266)	(0.00761)	(0.00333)	(0.00182)

Note: Reported are the results from estimating equation (4): log of the FHFA housing price index (HPI) for the census tract is regressed on the neighborhood shares of SF rentals and other housing units (OHUs), along with controls for year, neighborhood demographics and non-residential properties. All regressions also include time averages of exogeneous variables and inverse Mills ratio from the probit model for each year. In Panel B, SF rentals are broken down into less (LE) and more (ME) expensive. In Panel C, SF rentals are broken down into four categories defining the home location of the owner. Standard errors clustered at the tract level and corrected for the first-step estimation of the selection equation are in parentheses. *, **, *** indicate significance at the 10, 5, and 1 percent levels, respectively.

Table 4 Results from estimating HPI models for the second set of sample divisions.

	Panel A Neighborhood Density		
	Low	Middle	High
SF rentals	-0.00997***	-0.02072***	-0.02810**
	(0.00375)	(0.00572)	(0.01289)
OHUs	-0.00285*	-0.00335**	-0.00162
	(0.00147)	(0.00144)	(0.00223)

	Panel B Type of Rental by Owner Location and Corporate Status
SF rentals	
Out of state	
Corp	0.03341
	(0.07096)
Non-Corp	-0.00853
	(0.02116)
In state	
Corp	-0.03908
	(0.04285)
Non-Corp	-0.03445***
	(0.00958)
OHUs	-0.00449**
	(0.00174)

Note: Reported are the results from estimating equation (4): log of the FHFA housing price index (HPI) for the census tract is regressed on the neighborhood shares of SF rentals and other housing units (OHUs), along with controls for year, neighborhood demographics and non-residential properties. Both regressions also include time averages of exogeneous variables and inverse Mills ratio from the probit model for each year. Standard errors clustered at the tract level and corrected for the first-step estimation of the selection equation are in parentheses. *, **, *** indicate significance at the 10, 5, and 1 percent levels, respectively.

Appendix Table A.1 Complete set of estimates of Panel A of Table 3 model.

	All Neigh	City	Suburbs	Income		
				Low	Middle	High
SF rentals	-0.01899***	-0.01095**	-0.01934***	-0.03030***	-0.01223***	-0.01401**
	(0.00397)	(0.00602)	(0.00494)	(0.00865)	(0.00467)	(0.00599)
OHUs	-0.00271**	-0.00306**	-0.00167	-0.00638**	-0.00465**	0.00064
	(0.00120)	(0.00166)	(0.00162)	(0.00265)	(0.00200)	(0.00129)
Black25	-0.01214***	-0.01345***	-0.01267***	-0.00484	-0.01323***	-0.01300***
	(0.00165)	(0.00240)	(0.00212)	(0.00298)	(0.00386)	(0.00422)
White25	-0.00997***	-0.01129***	-0.00985***	-0.00463**	-0.00860***	-0.00357*
	(0.00094)	(0.00154)	(0.00114)	(0.00227)	(0.00199)	(0.00183)
Black50	-0.00962***	-0.01188***	-0.00808***	-0.00403*	-0.01533***	-0.00584*
	(0.00123)	(0.00204)	(0.00152)	(0.00219)	(0.00238)	(0.00318)
White50	-0.00932***	-0.01148***	-0.00829***	-0.00388**	-0.01148***	-0.00796***
	(0.00076)	(0.00116)	(0.00097)	(0.00192)	(0.00153)	(0.00125)
Black75	-0.01145***	-0.01654***	-0.01136***	-0.00856**	-0.00845**	-0.00998**
	(0.00213)	(0.00357)	(0.00260)	(0.00382)	(0.00342)	(0.00410)
White75	-0.01117***	-0.01295***	-0.01041***	-0.00969***	-0.01232***	-0.01139***
	(0.00120)	(0.00207)	(0.00142)	(0.00305)	(0.00230)	(0.00178)
Black125	-0.00791***	-0.02086***	-0.00418*	-0.01534***	0.00236	-0.01236***
	(0.00218)	(0.00407)	(0.00252)	(0.00441)	(0.00402)	(0.00352)
White125	-0.01044***	-0.00917***	-0.01056***	-0.00301	-0.01033***	-0.01413***
	(0.00121)	(0.00220)	(0.00143)	(0.00319)	(0.00231)	(0.00155)
Black125+	-0.01476***	-0.01877**	-0.01363***	-0.00278	-0.01164*	-0.02449***
	(0.00372)	(0.00857)	(0.00404)	(0.00890)	(0.00649)	(0.00518)
Store, one	0.00067	0.00187*	0.00030	-0.00013	0.00204	0.00272**
story	(0.00058)	(0.00102)	(0.00060)	(0.00078)	(0.00124)	(0.00116)
Mixed use	0.00095	0.00160*	0.00071	0.00069	0.00310***	-0.00072
	(0.00063)	(0.00089)	(0.00080)	(0.00081)	(0.00119)	(0.00102)
Dept. store	-0.02234***	-0.01897*	-0.01619**	-0.03062***	-0.02535***	-0.00635
	(0.00646)	(0.01127)	(0.00705)	(0.01103)	(0.00924)	(0.01134)
Supermarket	-0.00760*	-0.00959*	-0.00462	-0.01019*	0.00211	-0.02368**
	(0.00454)	(0.00571)	(0.00734)	(0.00597)	(0.00714)	(0.01020)
Restaurant	0.00277	-0.00417	0.00630**	0.00009	0.00365	-0.00037
	(0.00240)	(0.00361)	(0.00319)	(0.00373)	(0.00439)	(0.00386)
Service	0.03613***	0.02620***	0.03898***	0.03555***	0.01768**	0.06179***
station	(0.00472)	(0.00762)	(0.00593)	(0.00651)	(0.00739)	(0.01054)

Bar	0.00152	-0.00203	-0.00127	-0.00812	0.01180	0.02973**
	(0.00661)	(0.00867)	(0.00931)	(0.01116)	(0.00926)	(0.01457)
Rec. center	-0.03304***	-0.05532***	-0.02596***	-0.03321*	-0.07756***	-0.02319***
	(0.01157)	(0.01721)	(0.00989)	(0.01850)	(0.01716)	(0.00783)
Light mfg.	-0.00030**	-0.00090	-0.00027*	-0.00032	-0.00018	-0.00048**
	(0.00014)	(0.00111)	(0.00014)	(0.00041)	(0.00040)	(0.00021)
Bakery	-0.01664	0.02344	-0.04143	-0.03352	-0.01518	-0.01561
	(0.02074)	(0.03233)	(0.02579)	(0.02606)	(0.02960)	(0.04110)
Church	-0.01271***	-0.00722***	-0.01508***	-0.00840***	-0.01717***	-0.01629***
	(0.00127)	(0.00167)	(0.00131)	(0.00162)	(0.00202)	(0.00258)
Private	0.00658	-0.00123	0.01043***	0.00297	0.01974***	0.00060
school	(0.00412)	(0.00613)	(0.00350)	(0.00584)	(0.00418)	(0.00565)
Wald test	113.93	48.97	72.55	52.61	54.88	26.72
p-value	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

Note: Reported are the results from estimating equation (4). SF rentals are the share of single-family homes offered for rent as a percentage of all housing units located in the neighborhood (census tract). OHU stands for the share of other housing units located in the neighborhood. Black25=% of neighborhood households with black head and annual income of $25,000 or less, Black50=% of neighborhood households with black head with annual income more than $25,000 and less than or equal to $50,000, Black75=% of neighborhood households with black head and annual income of more than $50,000 and less than or equal to $75,000. Black125=% of neighborhood households with a black head and annual income of more than $75,000 and less than or equal to $125,000. Black125+ is the percent of neighborhood households with black head and an annual income more than $125,000. The variables for white household heads are similarly defined. White households with annual incomes exceeding $125,000 is the reference group. All regressions also include year dummies, time averages of exogeneous variables, and inverse Mills ratio from the probit model for each year. These estimates are not shown to save space. The bottom of the table reports the Wald test statistic for joint significance of the inverse Mills ratios. The *p*-value of the associated Wald test is in square bracket. Standard errors clustered at the tract level and corrected for the first-step estimation of the selection equation are in parentheses. *, **, *** indicate significance at the 10, 5, and 1 percent levels, respectively.

Appendix Table A.2 Complete set of estimates of Panel B of Table 3 model.

	All Neigh	City	Suburbs	Income		
				Low	Middle	High
SF rentals						
LE	-0.01940***	-0.02141**	-0.01394*	-0.02461**	-0.01077*	-0.01558
	(0.00639)	(0.00918)	(0.00742)	(0.01064)	(0.00634)	(0.02458)
ME	-0.02385**	0.00605	-0.03671***	-0.04007	-0.01417	-0.01920
	(0.01060)	(0.01849)	(0.01384)	(0.03352)	(0.01423)	(0.01977)
OHUs	-0.00288**	-0.00370**	-0.00205	-0.00527**	-0.00472**	0.00070
	(0.00128)	(0.00181)	(0.00195)	(0.00243)	(0.00224)	(0.00141)
Black25	-0.01122***	-0.00978***	-0.01289***	-0.00683*	-0.01238**	-0.01366**
	(0.00181)	(0.00321)	(0.00224)	(0.00387)	(0.00516)	(0.00553)
White25	-0.00998***	-0.00795***	-0.01143***	-0.00650*	-0.00823**	-0.00291
	(0.00173)	(0.00279)	(0.00211)	(0.00395)	(0.00344)	(0.00242)
Black50	-0.00940***	-0.00857***	-0.00906***	-0.00593	-0.01479***	-0.00473
	(0.00168)	(0.00319)	(0.00202)	(0.00369)	(0.00337)	(0.00337)
White50	-0.00893***	-0.00970***	-0.00828***	-0.00565*	-0.01069***	-0.00724***
	(0.00098)	(0.00165)	(0.00119)	(0.00299)	(0.00184)	(0.00169)
Black75	-0.01175***	-0.01200**	-0.01357***	-0.01161	-0.00757*	-0.01010
	(0.00304)	(0.00472)	(0.00380)	(0.00736)	(0.00440)	(0.00875)
White75	-0.01089***	-0.01132***	-0.01076***	-0.01150***	-0.01181***	-0.01049***
	(0.00141)	(0.00225)	(0.00171)	(0.00420)	(0.00323)	(0.00284)
Black125	-0.00920***	-0.02240***	-0.00688**	-0.01670***	0.00189	-0.01267***
	(0.00236)	(0.00440)	(0.00316)	(0.00492)	(0.00467)	(0.00376)
White125	-0.01092***	-0.01074***	-0.01110***	-0.00272	-0.01065***	-0.01430***
	(0.00129)	(0.00234)	(0.00163)	(0.00317)	(0.00311)	(0.00219)
Black125+	-0.01589***	-0.01963**	-0.01371***	-0.00568	-0.01300**	-0.02400***
	(0.00376)	(0.00916)	(0.00425)	(0.01161)	(0.00651)	(0.00610)
Store, one	0.00066	0.00256**	0.00024	0.00002	0.00233	0.00272**
story	(0.00061)	(0.00121)	(0.00063)	(0.00083)	(0.00144)	(0.00121)
Mixed use	0.00184**	0.00162	0.00218*	0.00115	0.00375***	0.00061
	(0.00085)	(0.00106)	(0.00114)	(0.00120)	(0.00141)	(0.00182)
Dept. store	-0.01667**	-0.02501	-0.01056	-0.02694**	-0.02216**	0.00089
	(0.00687)	(0.01559)	(0.00747)	(0.01245)	(0.00997)	(0.01088)
Supermarket	-0.01006*	-0.00545	-0.01292	-0.01483	-0.00017	-0.02452**
	(0.00549)	(0.00808)	(0.00881)	(0.00991)	(0.00889)	(0.01052)
Restaurant	0.00315	-0.00630	0.01022**	0.00146	0.00238	-0.00026

	(0.00293)	(0.00393)	(0.00463)	(0.00500)	(0.00614)	(0.00434)
Service	0.03457***	0.02484***	0.03316***	0.03212***	0.02059***	0.05935***
station	(0.00526)	(0.00816)	(0.00762)	(0.01028)	(0.00749)	(0.01516)
Bar	0.00422	-0.00348	0.00214	-0.00520	0.01150	0.03003
	(0.00704)	(0.00909)	(0.01093)	(0.01190)	(0.01008)	(0.01875)
Rec. center	-0.03172**	-0.04944***	-0.01653	-0.02917	-0.07844***	-0.02090
	(0.01328)	(0.01872)	(0.01335)	(0.02077)	(0.01785)	(0.01390)
Light mfg.	-0.00036***	0.00035	-0.00033***	-0.00046	-0.00038	-0.00053***
	(0.00013)	(0.00164)	(0.00013)	(0.00044)	(0.00046)	(0.00020)
Bakery	-0.01582	0.02759	-0.04116*	-0.03103	-0.01374	-0.01001
	(0.02092)	(0.03038)	(0.02465)	(0.02722)	(0.02984)	(0.03886)
Church	-0.01300***	-0.00654***	-0.01574***	-0.00842***	-0.01736***	-0.01779***
	(0.00134)	(0.00161)	(0.00145)	(0.00187)	(0.00209)	(0.00494)
Private	0.00565	-0.00018	0.00738	0.00336	0.01932***	0.00023
school	(0.00438)	(0.00647)	(0.00504)	(0.00579)	(0.00461)	(0.00571)
Wald test	106.64	44.88	54.93	53.53	54.17	16.66
p-value	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

Note: SF rentals are broken down into less (LE) and more (ME) expensive. See also the note to Table A.1.

Appendix Table A.3 Complete set of estimates of Panel C of Table 3 model.

	All Neigh	City	Suburbs	Income		
				Low	Middle	High
SF rentals						
Zip	-0.03404***	-0.02353**	-0.04335**	-0.08597**	-0.05687***	0.02221
code	(0.01048)	(0.00964)	(0.01881)	(0.03430)	(0.01651)	(0.01920)
County	-0.03478***	-0.02272	-0.04189**	-0.08616***	-0.04247***	0.02117
	(0.00946)	(0.01814)	(0.01713)	(0.03117)	(0.01371)	(0.02107)
State	-0.03624***	-0.02253**	-0.05012***	-0.08468*	-0.04739***	0.01224
	(0.00949)	(0.00965)	(0.01762)	(0.04516)	(0.01386)	(0.01862)
Out of	0.00223	-0.01608	0.00858	-0.03115	-0.01815**	0.04389**
state	(0.00762)	(0.01739)	(0.00954)	(0.02064)	(0.00870)	(0.01982)
OHUs	-0.00406**	-0.00531**	-0.00366	-0.01743**	-0.00961***	0.00226
	(0.00177)	(0.00217)	(0.00266)	(0.00761)	(0.00333)	(0.00182)
Black25	-0.00978***	-0.01196***	-0.00817**	0.00266	-0.00737*	-0.01862***
	(0.00232)	(0.00269)	(0.00374)	(0.00585)	(0.00435)	(0.00515)
White25	-0.00788***	-0.00953***	-0.00641**	-0.00061	-0.00652***	-0.00832***
	(0.00154)	(0.00188)	(0.00254)	(0.00383)	(0.00234)	(0.00309)
Black50	-0.00829***	-0.01065***	-0.00587**	-0.00181	-0.01275***	-0.00849**
	(0.00162)	(0.00223)	(0.00251)	(0.00279)	(0.00276)	(0.00416)
White50	-0.00784***	-0.00975***	-0.00599**	-0.00091	-0.00829***	-0.01244***
	(0.00134)	(0.00139)	(0.00235)	(0.00304)	(0.00203)	(0.00245)
Black75	-0.00977***	-0.01392***	-0.00877***	-0.00625	-0.00691*	-0.01505**
	(0.00236)	(0.00374)	(0.00311)	(0.00500)	(0.00370)	(0.00584)
White75	-0.01060***	-0.01111***	-0.00938***	-0.00838**	-0.00946***	-0.01904***
	(0.00155)	(0.00231)	(0.00213)	(0.00387)	(0.00273)	(0.00363)
Black125	-0.00860***	-0.01915***	-0.00571**	-0.01985***	-0.00100	-0.01710***
	(0.00225)	(0.00412)	(0.00277)	(0.00570)	(0.00425)	(0.00472)
White125	-0.01089***	-0.00905***	-0.01108***	-0.00588	-0.01018***	-0.01621***
	(0.00126)	(0.00220)	(0.00157)	(0.00407)	(0.00260)	(0.00191)
Black125+	-0.01639***	-0.02191**	-0.01498***	-0.01003	-0.01168*	-0.02282***
	(0.00414)	(0.00890)	(0.00467)	(0.01143)	(0.00707)	(0.00635)
Store, one	0.00071	0.00197*	0.00034	0.00132	0.00181	0.00203
story	(0.00061)	(0.00102)	(0.00068)	(0.00110)	(0.00136)	(0.00126)
Mixed use	0.00193***	0.00284***	0.00158*	0.00281*	0.00485***	-0.00153
	(0.00072)	(0.00107)	(0.00092)	(0.00148)	(0.00121)	(0.00153)
Dept. store	-0.01667**	-0.01872	-0.00811	-0.02497	-0.02108**	-0.00858

	(0.00682)	(0.01233)	(0.00800)	(0.01613)	(0.01036)	(0.01410)
Supermarket	-0.00907*	-0.00712	-0.01001	-0.00256	0.00077	-0.03129***
	(0.00468)	(0.00615)	(0.00799)	(0.00794)	(0.00786)	(0.01162)
Restaurant	0.00338	-0.00328	0.00680*	-0.00003	0.01176**	-0.00077
	(0.00266)	(0.00372)	(0.00382)	(0.00435)	(0.00574)	(0.00448)
Service	0.03511***	0.02486***	0.03715***	0.02245**	0.01346*	0.08641***
station	(0.00568)	(0.00794)	(0.00814)	(0.00979)	(0.00799)	(0.01596)
Bar	0.00540	-0.00106	0.00880	0.00023	0.01797*	0.00995
	(0.00693)	(0.00899)	(0.01097)	(0.01123)	(0.01080)	(0.01719)
Rec. center	-0.03314***	-0.05407***	-0.02737**	-0.04791	-0.09440***	-0.04675***
	(0.01223)	(0.01824)	(0.01248)	(0.03029)	(0.02251)	(0.01348)
Light mfg.	-0.00034**	-0.00110	-0.00028**	-0.00105*	-0.00047	-0.00058**
	(0.00014)	(0.00121)	(0.00014)	(0.00056)	(0.00054)	(0.00026)
Bakery	-0.01277	0.01384	-0.03537	-0.03588	-0.01315	-0.03945
	(0.02140)	(0.03143)	(0.02796)	(0.02839)	(0.03066)	(0.04710)
Church	-0.01158***	-0.00703***	-0.01290***	-0.00610***	-0.01568***	-0.01630***
	(0.00123)	(0.00173)	(0.00155)	(0.00192)	(0.00184)	(0.00258)
Private	0.00753*	-0.00133	0.01268***	0.00318	0.02273***	0.00252
school	(0.00426)	(0.00558)	(0.00405)	(0.00550)	(0.00303)	(0.00640)
Wald test	147.26	51.01	88.02	42.30	42.04	28.92
p-value	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

Note: SF rentals are broken down into four categories defining the home location of the owner. See also the note to Table A.1.

Appendix Table A.4 Complete set of estimates of Table 4 model.

	Neighborhood Density			
	Low	Middle	High	
	(1)	(2)	(3)	(4)
SF rentals	-0.00997***	-0.02072***	-0.02810**	
	(0.00375)	(0.00572)	(0.01289)	
Out of state				
Corp				0.03341
				(0.07096)
Non-Corp				-0.00853
				(0.02116)
Local				
Corp				-0.03908
				(0.04285)
Non-Corp				-0.03445***
				(0.00958)
OHUs	-0.00285*	-0.00335**	-0.00162	-0.00449**
	(0.00147)	(0.00144)	(0.00223)	(0.00174)
Black25	-0.01066***	-0.01545***	-0.01405***	-0.00931***
	(0.00264)	(0.00244)	(0.00297)	(0.00228)
White25	-0.01198***	-0.01159***	-0.00994***	-0.00785***
	(0.00126)	(0.00157)	(0.00165)	(0.00150)
Black50	-0.00815***	-0.01126***	-0.00995***	-0.00851***
	(0.00198)	(0.00194)	(0.00233)	(0.00200)
White50	-0.00797***	-0.00910***	-0.00884***	-0.00776***
	(0.00105)	(0.00122)	(0.00159)	(0.00131)
Black75	-0.02028***	-0.01047***	-0.01184***	-0.01102**
	(0.00324)	(0.00364)	(0.00294)	(0.00461)
White75	-0.01090***	-0.00995***	-0.00889***	-0.01056***
	(0.00153)	(0.00180)	(0.00259)	(0.00164)
Black125	-0.00839***	-0.01998***	-0.00717**	-0.00963***
	(0.00321)	(0.00364)	(0.00310)	(0.00292)
White125	-0.01056***	-0.00849***	-0.00473**	-0.01138***
	(0.00155)	(0.00176)	(0.00202)	(0.00145)
Black125+	-0.00995*	-0.00897	-0.01507***	-0.01735***
	(0.00556)	(0.00648)	(0.00543)	(0.00453)
Store, one	-0.00109*	0.00036	0.00128	0.00063

story	(0.00062)	(0.00099)	(0.00108)	(0.00067)
Mixed use	0.00221***	0.00074	0.00141	0.00182**
	(0.00074)	(0.00122)	(0.00105)	(0.00077)
Dept. store	-0.01365*	-0.01256	0.00297	-0.01719**
	(0.00719)	(0.00947)	(0.01153)	(0.00721)
Supermarket	0.00114	-0.00641	-0.02029**	-0.01137
	(0.00640)	(0.00587)	(0.00900)	(0.00912)
Restaurant	0.01053***	0.00317	-0.00593	0.00402
	(0.00321)	(0.00322)	(0.00482)	(0.00371)
Service	0.01249**	0.03750***	0.02573***	0.03418***
station	(0.00592)	(0.00637)	(0.00976)	(0.00709)
Bar	0.00416	0.00690	0.00349	0.00590
	(0.01066)	(0.01128)	(0.00775)	(0.00708)
Rec. center	-0.01042**	-0.05165***	-0.02067	-0.02899*
	(0.00521)	(0.01970)	(0.02729)	(0.01640)
Light mfg.	0.00040	-0.00013	-0.00090	-0.00032**
	(0.00039)	(0.00017)	(0.00057)	(0.00013)
Bakery	-0.00255	0.00558	0.03133	-0.01197
	(0.01595)	(0.03682)	(0.06390)	(0.02167)
Church	-0.00686***	-0.00322*	-0.00237	-0.01128***
	(0.00122)	(0.00186)	(0.00283)	(0.00175)
Private	0.00778	0.00504	-0.00241	0.00714
school	(0.00544)	(0.00486)	(0.00783)	(0.00457)
Wald test	37.11	13.68	42.22	109.34
p-value	[0.000]	[0.033]	[0.000]	[0.000]

Note: In Column (4), SF rentals are broken down into four categories depending on owner location and corporate status. See also the note to Table A.1.

Appendix Table A.5 Results for first-stage diagnostics of 2SLS estimation of Table 3 models.

	Standard *F*-statistic	SW *F*-statistic
	Panel A	
All Neighborhoods	224.00	
City	129.45	
Suburbs	120.29	
Low income	96.73	
Middle income	107.25	
High income	45.30	
	Panel B	
All Neighborhoods		
LE	74.58	22.61
ME	21.02	18.62
City		
LE	32.02	4.33
ME	8.36	3.61
Suburbs		
LE	61.77	17.55
ME	13.01	15.05
Low income		
LE	29.26	6.70
ME	3.32	2.82
Middle income		
LE	78.73	11.11
ME	15.44	11.15
High income		
LE	26.20	4.67
ME	11.68	4.52
	Panel C	
All Neighborhoods		
Zip code	192.85	91.60
County	55.33	95.17
State	152.56	113.84
Out of state	41.44	119.47
City		
Zip code	98.31	65.07

County	19.39	28.90
State	75.87	45.23
Out of state	24.94	35.81
Suburbs		
Zip code	162.90	31.91
County	57.09	31.56
State	92.28	34.33
Out of state	29.17	82.81
Low income		
Zip code	110.25	8.97
County	64.26	10.37
State	36.01	8.86
Out of state	27.88	65.91
Middle income		
Zip code	55.89	29.88
County	30.64	36.65
State	69.37	43.73
Out of state	48.95	91.90
High income		
Zip code	63.45	28.86
County	17.33	26.37
State	60.22	33.82
Out of state	10.03	21.76

Note: Reported are the first-stage 2SLS results from estimating equation (1): log of the FHFA housing price index (HPI) for the census tract is regressed on the neighborhood shares of SF rentals and other housing units (OHUs), along with year and neighborhood fixed effects, neighborhood demographics and non-residential properties. In Panel B, SF rentals are broken down into less (LE) and more (ME) expensive. In Panel C, SF rentals are broken down into four categories defining the home location of the owner. The Standard *F*-statistic is the Kleibergen-Paap (2007) Wald *rk* F statistic that is robust to clustering. The SW *F*-statistic refers to the Sanderson-Windmeijer (2016) conditional *F* statistic, which is used for testing weak identification of each endogenous regressor separately in the case of multiple endogenous variables (Panels B and C). In the case of a single endogenous regressor (Panel A), the SW *F*-statistic is identical to the Standard *F*-statistic and hence omitted from the table.

Appendix Table A.6 Results for first-stage diagnostics of 2SLS estimation of Table 4 models.

	Standard *F*-statistic	SW *F*-statistic
	Panel A	
Low density	204.99	
Medium density	94.54	
High density	30.94	
	Panel B	
Individual owned, in state	26.52	54.73
Individual owned, out of state	51.83	24.61
Corporate owned, in state	3.90	18.63
Corporate owned, out of state	13.16	25.40

Note: Reported are the first-stage 2SLS results from estimating equation (1): log of the FHFA housing price index (HPI) for the census tract is regressed on the neighborhood shares of SF rentals and other housing units (OHUs), along with year and neighborhood fixed effects. The Standard *F*-statistic is the Kleibergen-Paap (2007) Wald *rk* F statistic that is robust to clustering. The SW *F*-statistic refers to the Sanderson-Windmeijer (2016) conditional *F* statistic, which is used for testing weak identification of each endogenous regressor separately in the case of multiple endogenous variables (Panel B). In the case of a single endogenous regressor (Panel A), the SW *F*-statistic is identical to the Standard *F*-statistic and hence omitted from the table.