Not In My Neighborhood: The Effects of Residential Rentals on Single-Family Home Values

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Abstract

Single-family homeowners have long expressed a distaste for residential rentals in their neighborhood based on a belief that rentals will adversely affect neighborhood quality and lower house values. Prior study of this issue is thin and has not been able to establish causality from correlation. In this paper, I utilize a twelve-year panel of neighborhoods from the Miami, Florida metropolitan area to study the impacts that four different types of rentals have on the values of single-family homes. Causality is more firmly established in comparison to previous research by estimating house value models that include time and neighborhood fixed effects and that treat the rentals as endogenous variables. My results show that, regardless of the type of rental, adding an additional rental unit to the neighborhood or increasing its neighborhood share at the expense of single-family owner-occupied homes, lowers home values, especially if the rental unit is of lower quality

1. Introduction

Single-family (SF) homeowners have traditionally fought the entry of land uses other than SF owner-occupied homes into their neighborhood. Their concern has been that these land uses, being out of character with the neighborhood, would depress the values of their homes. In recent years, SF homeowner concerns have especially been focused on possible negative spillover effects from residential rentals, which have increased within many urban neighborhoods.[1] Spillovers mentioned include negative sight externalities from poor upkeep, automobile congestion, and neighborhood crime. The lion's share of the growth in rentals has resulted from the conversion of owner-occupied SF homes into rentals.[2] While perhaps less of a concern to homeowners than having multifamily (MF) housing within their neighborhood, SF rentals have also elicited the ire of many property owners.[3] However, there is little evidence suggesting that rentals, whether they are apartments, condominiums, mobile homes or SF homes, depress the values of nearby SF homes. Much of the evidence that does exist has not been able to clearly establish causality from correlation due to a reliance on cross-sectional data. In this paper, I utilize a twelve-year panel of neighborhoods from the Miami, Florida metropolitan area to study the impacts that the above different types of rentals have on the values of SF homes. To my knowledge, this is the first paper offering evidence on these comparative effects. Causality is more

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[1] Based upon property tax records from Florida, Ihlanfeldt et al. (2018) show that on average across Florida's urban counties the share of housing units represented by rentals increased six percentage points from 42 percent in 2000 to 48 percent in 2014, while the growth in the SF rental share increased seven percentage points from 15 to 22 percent. Based on their own calculations using data from the American Community Survey (ACS), the authors found that the rental share at the national level measured over a shorter period (2005—2014) grew from 33.1 to 36.9 percent, while the share of SF rentals grew from 10.2 to 12.9 percent. They note that the ACS does not report the rental shares broken down by urban versus rural areas, but based on their findings from Florida the increase in the shares of rentals for urban areas nationally is expected to be much greater than for urban and rural areas combined. Ihlanfeldt and Yang (2019) report that for Miami-Dade County, one of the three counties included in the panel data I use in this paper, 65% and 58% of the block groups experienced an increase in all rentals and SF rentals, respectively, as a share of the housing stock between 2006 and 2016.

[2] Much of the investment in SF rentals has originated from institutional investors (Smith and Liu, 2017; Mills et al., 2016). Mills et al. (2016) conclude that these investors are in for the long haul and do not intend to liquidate their rental holdings anytime soon. This suggests that SF rentals in neighborhoods are here to stay.

[3] The results from surveys of homeowners revealing their distaste for SF rentals are reported by Dewan (2013), Fottrell (2013) and Kremer (2010). Yoder (2012) reports that a growing number of cities have started enacting "rental density" limits that restrict the number of SF rental properties in a given area.

firmly established in comparison to previous research by estimating house value models that include time and neighborhood fixed effects and that treat the rentals as endogenous variables. Included as control variables are a wide range of different types of commercial and industrial properties.

Specifically, I use my neighborhood panel to relate the Federal Housing Finance Agency's (FHFA) House Price Index (HPI) for census tracts to the number of SF homes, apartments, condominiums, and mobile homes, broken down by housing tenure, within the tract. Because it is not clear whether it is the number of these units or their share of the neighborhood's housing stock that may affect SF home values, I alternatively measure the different types of housing units in counts and in shares in estimating my models. Models are also estimated that differentiate, by tenure, less expensive from more expensive units.

My results show that, regardless of the type of rental, adding an additional rental unit to the neighborhood or increasing its neighborhood share at the expense of SF owner-occupied homes, lowers SF home values, especially if the rental unit is of lower quality. Apparently, homeowner concerns regarding the value deflating effects of rentals are not without merit. This conclusion has an important bearing on local land use planning and regulation and sets the stage for further research to identify the exact pathways whereby rentals produce their negative effects. After discussing these possible pathways in section 2, the sparse literature relevant to my study is reviewed in section 3. My panel data and estimated house value equations are presented in sections 4 and 5, respectively. The next two sections (6 and 7) report values of selected descriptive statistics and my results. Section 8 concludes the paper providing the policy implications of this study and suggestions for future research.

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

My purpose is limited to addressing the question of whether rentals impact single-family home values. The exact mechanisms underlying possible effects are not investigated. However, some background on these likely mechanisms serves to motivate my analysis. There are three possible pathways that may cause rentals to lower neighborhood SF home values. In this section I describe these pathways and review prior literature providing evidence on their existence.

2.A Neighborhood Character

Although the character of a neighborhood can mean many things, in the minds of many homeowners it is strongly related to the composition of housing types found within their neighborhood. The look of a neighborhood with exclusively SF homes differs from one with a mix of SF homes and certain other types of residential units. Mobile homes and MF housing (both apartments and condominiums) may detract from the appearance of the neighborhood simply because of their obvious physical differences from SF homes. MF housing, which is frequently multi-storied, may also impede air flow, views and sunshine. I am unaware of any evidence relevant to this pathways effect on neighborhood housing values.

2.B Maintenance and Appearance

A number of studies have found that rentals are less well maintained than owner-occupied housing (Galster, 1983; Shilling et al., 1991; Harding et al., 2000). Because renters enjoy only a consumption and not an investment return on 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.

2.C Crime

Rentals may increase neighborhood crime for a number of reasons. 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. I was unable to find any evidence on the relationship between crime and rentals other than the results of my prior research with others (Ihlanfeldt et al., 2018). Our crime data (a ten-year panel at the block group level) came from Miami-Dade County. We estimated control function Poisson models, regressing the number of crimes within a block group on a set of housing types similar to those I use in this study, along with year and neighborhood fixed effects. We found increases in SF and apartment rentals as shares of a neighborhood's housing stock increase the number of property crimes. Because a large number of studies have found that higher neighborhood crime results in lower housing values (Rizzo, 1979; Naroff et al., 1980; Burnell, 1988; Gibbons, 2004; Tita et al., 2006; Ihlanfeldt and Mayock, 2010), an increase in rentals may reduce house values through this pathway.

3. Literature Review

The literature that has focused on the effects of different types of housing units and their spillover effects on SF home values can be grouped into studies that focus on MF housing, SF rentals, and mobile homes. Each group is reviewed in this section.

3.A Multifamily Housing

Pollakowski et al. (2005) conducted the first study investigating the impact of apartments on SF home values. They selected seven large-scale, mixed income, MF developments located in the suburbs of Boston, Massachusetts. For each development they collected the sales prices of SF homes for the years 1983 to 2003 that fell within and outside of an area where sales prices were most likely to be impacted by the development. SF homes were found to appreciate no differently between the impact and control areas, leading them to conclude that the MF developments that they studied had no impact on SF home values.

Moody and Nelson (2007) conducted a much more comprehensive study of the impact of apartments on SF home values. Using 1995–2000 sales data from Gwinnett County, Georgia, they estimated two models—a standard hedonic price model, regressing the sales price of SF homes on network distances to apartment complexes and a neighborhood house price appreciation model, which included the percentage of housing units in the neighborhood that were apartments. Their results showed, on average, $301 in SF residential housing price is gained for every 1,000 feet from an apartment complex. When they differentiated apartment complexes by size and quality, they found that proximity to large, low quality complexes has the largest negative effects on house values. Their results from estimating their neighborhood house price appreciation model were unexpected. In neighborhoods where apartments are a larger share of the housing units, housing values increase more rapidly. They suggested that their counterintuitive results may have resulted from young households being attracted to neighborhoods with apartments, who after accumulating money for a down payment to buy a home chose to stay in the neighborhood and thereby drive up the demand for housing.

While these studies are informative, their mixed results and reliance on cross-sectional data still leave the issue of the impact of apartments on the values of SF homes unresolved.

3.B Single-Family Rentals

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 are relevant to the current study. However, their poor methodological design suggests they should receive scant attention. Haurin et al. (2002), Coulson et al. (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 et al., 2002 and 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 are comprised of 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.

The studies in this group 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. 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.

3.C Mobile Homes

The literature on mobile homes and their impact on SF home values is the thinnest of the groups covered in this section. No study has considered rental mobile homes. One study by Munneke and Slawson (1999) focuses on mobile home parks. Using 1990–1994 SF home transactions from East Baton Rouge Parish, Louisiana, they regressed sales price on proximity to a mobile home park, controlling for a standard set of structural and neighborhood attributes, along with a sample selection correction for whether mobile home parks were located in areas of relatively lower land values. They found that the value of a SF home within a quarter of a mile of a mobile home park is worth five percent less than a home located farther away (between a quarter and a half mile). A limitation of their study is that actual land values were not available, causing the authors to rely on possible correlates.

In summary, I have identified only six studies that seem to have relevance to my investigation of the effects that different types of rentals have on the prices of SF homes. This small number is surprising in light of the importance of the issue. In the eyes of many homeowners, rental housing represents NIMBYs (not-in-my-back-yard) and LULUs (locally undesirable land uses) that are believed to depress housing values. But is this true? If so, for all rentals or only certain types of rentals? Absence of interest in these questions fails to explain the paucity of prior research. Panel data at the neighborhood level containing information on house price and the tenure composition of the housing stock, which would facilitate a convincing causal analysis, have not been widely available. In the next section I describe my unique panel of neighborhoods within the Miami metropolitan area that I used to provide the first evidence on the comparative impacts of different types of rentals on SF home values.

4. Data

The panel that I use to estimate my house price models is constructed at the census tract level covering the years 2006–2017; however, as I describe below, to construct my instrumental variables I employ base year values going back four years before the beginning of the panel to 2002. The census tracts used to form my panel come from the three counties that constitute the Miami-Fort Lauderdale-West Palm Beach, FL MSA: Miami-Dade, Broward and Palm Beach Counties. There are a total of 1219 tracts within the MSA.

My empirical models relate the FHFA HPI for census tracts to counts of 7 different types of residential units located within the tract, and in an alternative specification, to the shares of each type as a percentage of the tract's total housing units. The HPI is a weighted, repeat-sales price index, measuring the movement of SF house prices from year to year.[4] It is based on transactions involving conforming, conventional mortgages purchased or securitized by Fannie Mae or Freddie Mac. 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. There is not an HPI for all of the 1219 tracts found within the Miami metropolitan area. In cases where there are an insufficient number of repeat sales to construct a reliable index no HPI is reported by the FHFA. This reduces the number of tracts available for my study to 849. As noted below, more tracts are dropped because the housing unit data are not available for all of the remaining tracts.

My 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 I selected the following residential units: apartments, SF homes, condominiums, and mobile homes. Also selected are counts of the following types of commercial/industrial properties: stand-alone store, mixed use, department store, supermarket, bar, bowling alley, light manufacturing, heavy manufacturing, lumberyard, cannery, warehouse, storage facility, church, private school, single office building, multiple office building, drive-in restaurant, restaurant, and gas service station. These counts serve as control variables in some of my estimated models.

What is most important for my 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 beneficial title to real property in [Florida] and who in good faith makes the property his or her permanent residence or the

[4] The census tract version of the HPI is described in Bogin et al. (2019). The methodology used to construct the HPI is covered in Calhoun (1996).

permanent residence of another or others legally or naturally dependent upon him or her." I use the presence of a homestead exemption to classify a property as owner-occupied, and housing units without a homestead exemption are classified as renter-occupied. Because the exemption provides significant tax savings, owner-occupants have strong financial incentives to file for the exemption, and I am thus confident that homestead status correctly classifies owner-occupied units, in general.[5] Properties not covered by a homestead exemption are primarily either rental units, vacant or second homes. The fraction of SF homes that are second homes is expected to be small because in Florida most vacation homes are condominiums. For condominiums I cannot rule out the possibility that some fraction of the properties I label as rentals may in fact be second homes not available for rent.

My housing typology consists of apartments within MF housing properties (all are rentals), SF homes, condominiums, and mobile homes. The latter three types are separated into owner-occupied and rentals using the homestead exemption. In some specifications of the models I estimate housing units are further broken down into less expensive (LE) and more expensive (ME).[6] Any such LE/ME breakdown is going to be arbitrary, but one reasonable choice would be to use the government's definition of an affordable unit. The Department of Housing and Urban Development (HUD) publishes a fair market rent (FMR) that defines an affordable unit for its program participants (HUD, 2007). FMRs are reported separately for each of the three counties represented in my panel for each year. To make the LE/ME breakdown I first imputed an annual rent for each unit.[7] A unit is designated as LE (ME) if the imputed rent is less than (greater than) HUD's FMR.

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[5] A homestead exemption decreases a property's taxable value by as much as $50,000.

[6] All of the housing types are divided into the number of LE and ME units, except mobile homes, where the total number was too small to make a meaningful separation.

[7] To calculate an imputed annual rent for each housing unit, I multiply an estimate of the rent-to-price ratio by the estimated market value of the property. The rent-to-price ratio is specific to each county and is estimated for each year of my panel. The data source is the Public Use Microdata Sample for the American Community Survey. Annual estimates of the market value of each property come from the property tax rolls. These 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.

The census tract reported for each of the properties on the tax rolls is the 2000 tract before the 2010 Census and the 2010 tract after the Census. To count the correct number of land uses within each tract for each year I needed the tract to stay the same before and after the Census. Hence, I only use tracts that fit this description. This further reduces the number of tracts in my panel from 849 to 457. The size of this reduction suggests that the tracts used may be unrepresentative of the neighborhoods found within the metro area. However, this is belied by the comparison of year 2010 means between the included and excluded tracts reported in Appendix Table A.1. Median incomes, racial percentages, owner-occupied percentages, and levels of education are all highly similar between the two groups of tracts.

My final panel is unbalanced because even for the tracts for which the FHFA reports an HPI for some years the HPI is missing, again due to an insufficient number of repeat sales. However, the number of tract/year observations remains large at 4,802.

5. Estimated House Price Equations

Two sets of equations are estimated. The first set of equations relates the natural log of the census tract HPI to counts of each type of residential unit and each type of commercial/industrial property, along with year and tract fixed effects. Formally,

$$\ln HPI_{i,t} = \gamma_t + \delta_i + \sum_{j=1}^{J} B_j H_{i,t,j} + \sum_{k=1}^{K} \alpha_k C_{i,t,k} + \varepsilon_{i,t} \,, \tag{1}$$

where i, t, j, and k represent tract, year, housing type, and commercial/industrial property, respectively. H is the number of units of the housing type and C is a count of the non-residential property type. There are seven housing types: SF owner-occupied and rental homes, condominium owner-occupied and rental homes, owner-occupied and rental mobile homes, and apartments. There are 20 non-residential property types, as listed in section 4. γ_t and δ_i are time fixed effects (year dummy variables) and tract fixed effects, respectively.

The second set of equations replace the residential counts with neighborhood shares. Formally,

$$\ln HPI_{i,t} = \gamma_t + \delta_i + \sum_{j=1}^{J} B_j S_{i,t,j} + \sum_{k=1}^{K} \alpha_k C_{i,t,k} + \varepsilon_{i,t}\ , \tag{2}$$

where i, t, and k and γ, δ, and C are the same as in (1). The type of housing share is j. S is the share of the housing unit as a percentage of the total number of housing units in the tract. The six housing shares are SF rentals, condo rentals and owner units, mobile home rentals and owner units, and apartments. The excluded share is for SF owner-occupied homes. Equations (1) and (2) are estimated with and without the C variables and the LE/ME breakdown of the housing types.

Although I include tract fixed effects to control for unobservable time-invariant heterogeneity affecting the HPI, it is likely that there are time-varying unobservables that are correlated with my housing variables that have their own impact on neighborhood crime. In fact, it may be these other factors that affect the HPI that account for the increase in rentals.[8] Hence, there is a need for instrumental variables (IV) for the housing types that satisfy strict exogeneity (i.e., variables that would be correlated with the housing counts (shares) that would not have their own influence on the HPI). Conceptually, it is reasonable to argue that a change in one of the housing types, say SF rentals, is driven by factors both within the neighborhood (FN) and county-wide (FC). While FN may be endogenous to the HPI, FC should not be affected by conditions within the home neighborhood, especially if the FC is 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 housing type (H) at the county level between the

[8] One possible set of other factors might be distressed properties (mortgage foreclosures and defaults, property tax delinquencies), which are not controlled for in my estimated models, due to the unavailability of data. Especially, mortgage foreclosures may be a factor, since prior studies have been shown that they reduce the values of nearby homes (for a review see Ihlanfeldt and Mayock, 2016). While instrumentation addresses problems that may arise from the omission of foreclosures from my models, results reported by Ihlanfeldt and Yang (2019) suggest that they are a very small percentage of the housing units within the census tracts included in my panel. They found that for Miami-Dade County the neighborhood percentage of REOs averaged over the years 2006-2012 equaled just .255.

base and current years, excluding the home neighborhood value. These percentage changes are then multiplied by the base year value of the housing type to obtain a prediction of the current year value ($\widehat{H}$), assuming the growth in the housing type followed the change that occurred at the county level. Formally,

$$\widehat{H}_{i,j,t} = H_{i,j,b} \times \left(1 + \frac{x - y}{x}\right), \tag{3}$$

where $x = H_{i,c,t} - H_{i,j,t}$, $y = H_{i,c,b} - H_{i,j,b}$, i indexes the type of housing unit, j indexes the census tract, t indexes the current year, b is the base year, and c represents the county. While HPI may affect $H_{i,j,t}$, it should not have an effect on $\widehat{H}_{i,j,t}$. However, the validity of $\widehat{H}_{i,j,t}$ as an instrument also depends on whether the neighborhood base year housing unit count can be treated as exogenous. For example, there may be an omitted variable that is correlated with the base year value (say the level of neighborhood crime) 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 crime effect and would not be orthogonal to the error term of my 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. I experimented with using base years that were 2 (2004), 3 (2003) and 4 (2002) years prior to the beginning of the panel. The results are robust to using these different base years. The results reported in my tables are those obtained with 2002 as the base year. While it is still possible that events 4 years prior to the beginning of the panel could affect the current HPI, this seems unlikely.

6. Descriptive Statistics

Table 1 shows the neighborhood means and standard deviations for HPI and its natural logarithm for each year of my panel. The movements of the means are as expected in light of the housing market crash and subsequent recovery. Mean HPIs trended downward from 2006 to 2012, falling 45%. After 2012 prices rose 71% and by 2017 had come almost all the way back to their pre-crash levels.

Neighborhood means and standard deviations of the housing units in counts and shares can be found in Table 2. Both overall means and means broken down by LE/ME are provided. Not surprisingly, SF owner-occupied units are a majority of the housing units within the average neighborhood (51.5%). Apartments have the next largest share (15.1%), followed by owner-occupied condominiums (13.2%). While apartments provide the largest share of rentals, rentals are also very present among SF homes and condominiums, together accounting for 19.7% of the total number of housing units in the average neighborhood. Mobile homes of both tenures have very small neighborhood shares, representing less than 1% on average.

The breakdowns by expenses show that among SF owner-occupied and rental homes the LE/ME split is roughly half and half. On the other hand, condominiums are much more likely to be in the LE category. Interestingly, among the apartment units most are of the more expensive variety.

7. Results

The results from estimating my first set of equations, where the housing units enter as neighborhood counts, are reported in Tables 3 and 4 where the types are not and are further broken down into LE/ME units, respectively. Corresponding tables (Tables 5 and 6) present the results obtained from estimating my second set of equations, where the housing units are measured as the shares of the total number of housing units within the neighborhood. Each of the results tables contains four columns. The first two columns are the OLS estimates, without and with the inclusion of the non-residential land uses as control variables. Similarly, the last two columns are the 2SLS estimates. For each of the housing variables I report the estimated coefficient, its standard error (in parentheses) and the exact percentage change (in brackets).[9] Also reported at the bottom of the tables is a chi-squared statistic, along with its *p*-value, that tests the endogeneity of the housing variables.[10] The null

[9] Exact percentage changes are calculated as: $\%\Delta HPI = 100 \cdot \left[exp\left(\hat{B}\right) - 1\right]$, where $\hat{B}$ is the estimated coefficient reported first in the tables for each housing type.

[10] The endogeneity test is the endog option available from Stata's ivreg2. The test is "defined

hypothesis is that the variables can actually be treated as exogenous, without the need for instrumentation.

For both sets of equations, the null hypothesis of the endogeneity test is strongly rejected indicating that the housing variables cannot be treated as exogenous. Nevertheless, it is instructive to compare the OLS and 2SLS estimates for their differences. Note that the 2SLS estimates are considerably larger than the OLS estimates. This is a common finding in empirical studies when the exogeneity of the regressors is rejected. As mentioned above, the OLS estimates may be downwardly biased by the omission from my models of unobservable neighborhood variables that have an effect on the HPI that are correlated with the housing variables.[11] On the other hand, the 2SLS estimates may be larger because of weak instruments. The statistic commonly used to detect weak instruments is the *F*-test of the joint significance of the instruments in the first-stage reduced form regression. In all cases, this statistic is significant at better than the one percent level. However, Baum et al. (2003) have shown that for models with multiple endogenous variables this test may not be sufficiently informative. More informative tests are the Sanderson-Windmeijer (2016) first-stage chi-squared and *F* statistics that test the under-identification and weak identification, respectively, of individual endogenous regressors. These statistics are constructed by "partialling-out" linear projections of the remaining endogenous regressors. I report these statistics in Appendix Tables A.2 and A.3 for my two sets of equations, respectively. For all of my housing variables, the null hypothesis that the variable is unidentified or weakly identified is strongly rejected.

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as the difference of two Sargan-Hansen statistics: one for the equation with the smaller set of instruments, where the suspect regressor(s) are treated as endogenous, and one for the equation with the larger set of instruments, where the suspect regressors are treated as exogenous. The estimated covariance matrix used guarantees a non-negative test statistic."

[11] The OLS estimates seem implausibly small. For example, the largest negative effect on the HPI is registered by SF rentals, where an additional unit results in only a .05% decline in house value. For the average SF home in Miami-Dade County in 2010 ($250,000), this translates to a $125 decline in house value. In comparison to the 2SLS estimates, the OLS estimates are also less intuitive. As examples, owner-occupied mobile homes have a larger negative effect on house value than those that are rentals and less expensive SF owner-occupied homes have a larger positive effect on house value than those that are more expensive.

Results from the estimation of my first set of equations, which measure the housing units in counts are reported in Table 3 (without the LE/ME breakdown) and Table 4 (with the LE/ME breakdown). Including the non-residential control variables as explanatory variables has little effect on my 2SLS estimates; hence, I will focus on the simpler models in column 3 of the tables that exclude these variables. My interest is in the effects of the four types of rentals units. All four types are found to reduce the HPI, with SF and mobile home rentals statistically significant at better than the 5% level and condominium rentals just marginally insignificant at the 10% level. The apartment rentals effect is not significant, which may reflect the fact that most of these units are of higher quality. A unit increase in SF rentals and mobile home rentals reduces the HPI by .17% and .22%, respectively. For the mean valued home in the metropolitan area ($250,000) in 2010, these percentages changes imply decreases in value of $425 and $550, respectively. These results suggest that rental units lower neighborhood house values, but not uniformly across all four types of rentals.

One other of the housing types has a statistically significant effect on the HPI, SF owner-occupied units; however here the effect is positive, suggesting that adding a new home to the neighborhood improves neighborhood quality. The results obtained from dividing the housing units into LE and ME show that expense matters little to the negative impacts that SF and condominium rentals have on the HPI, but that LE but not ME apartment units produce a negative and highly significant effect on the HPI. An additional LE apartment reduces the HPI by .05%. While seemingly a small effect, the average large MF property in the Miami MSA has 60 apartments, which if added to a neighborhood would reduce house value by 3%, an economically meaningful effect.[12]

The LE/ME estimates also showed some differences for SF and condominium owner-occupied units. SF homes in the LE group have a negative and statistically significant effect on house value, with an additional unit reducing house value by .04%. The estimate for ME SF units is positive and

[12] The FDOR tax rolls divide MF properties into small (those with fewer than 8 apartments) and large (those with more than 8 apartments). The 60 unit mean is based on the latter grouping.

insignificant. These results suggest, unsurprisingly, that neighbors prefer having nicer homes added to their neighborhood. Opposite and perplexing results are obtained from the LE/ME split for owner-occupied condominiums, which show that ME but not LE units reduce neighborhood house value. This may reflect the ME units being in larger, more obtrusive buildings; however, my data do not allow an investigation of this possibility.

In summary, the key takeaway from the estimation of my first set of neighborhood house value equations is that except for condominium rentals, adding one of the other three types of rentals (SF, mobile home, and apartment) reduces the HPI. Mobile home rentals are found to have the most pernicious effect on a per unit basis, but the typical sized MF project, if of lower quality, apparently can cause a troublesome loss in neighborhood quality. All in all, my results seem plausible and confirm the conclusions of earlier studies (reviewed above) that find SF property values are adversely affected by having more SF or MF rentals in the neighborhood.

In my second set of equations the measurement of the housing types is in shares rather than units. So now the question addressed is different; namely, if the composition of the housing units in a neighborhood shifts away from owner-occupied SF homes in favor of the various types of rentals, how does this affect the neighborhood HPI? The contrasts between the OLS and 2SLS results from estimating my first set of equations carry over to my second set of equations and again the null hypothesis of regressor exogeneity is strongly rejected.

Also similar between the two sets of equations is that the results are robust to the exclusion/inclusion of the non-residential land uses as control variables; hence, again I will focus on the results obtained with the simpler 2SLS models that include only the housing shares (with the share of owner-occupied SF housing serving as the reference category), along with the neighborhood and year fixed effects.

Tables 5 and 6 present the results obtained without and with the LE/ME breakdown, respectively. The results in both tables lend considerable credence to the belief of many SF homeowners that altering the residential makeup of their neighborhood away from SF owner-occupied homes will lessen the appeal of the neighborhood and lower property values. Remarkably, Table 5 shows that regardless of the housing type, increasing its neighborhood share at the expense of owner-occupied SF homes lowers the HPI. Increasing the shares of SF rentals or mobile homes (regardless of their tenure) have the largest negative effects on the HPI, causing roughly a 5 percent decrease in the HPI. To assess the reasonableness of this magnitude, some idea of the number of homes represented by a one percentage point increase in the share is needed. This translates to about 26 units for the average neighborhood in my sample; hence, a 5 percent decline is within reason. For the other housing types—condominium rentals and owner-occupied units, and apartments—the reduction in the HPI is between 1 to 2 percent. Again, these magnitudes are plausible. One would expect that 26 additional SF rentals or mobile homes in the neighborhood (replacing the same number of SF owner-occupied units) would produce a larger negative effect on the HPI than 26 more condominiums or apartments.

The LE/ME results (Table 6) tell basically the same story as those in Table 5, except that if the SF rentals or the condominium rentals are in the ME as opposed to LE group, increasing their share does not cause a decline in the HPI. Again, there is intuition in these results.

8. Conclusion

Owners of SF homes have fought the intrusion of rentals into their neighborhood largely because they fear a loss in their property value. These fears have resulted in land use regulations limiting rentals, as well as various acts of nimbyism directed at rentals. Unfortunately, the evidence linking rentals to property values has simply been too thin to determine whether the fears of homeowners are factual. In this paper I have provided the first empirical analysis that quantifies the impacts of different types of rentals on SF home values. My argument for causality over correlation is buttressed by the use of panel data allowing me to control for both unobserved heterogeneity across neighborhoods and over time within neighborhoods. Moreover, my results are robust to the addition of an extensive set of non-residential land uses to my estimated models. Adding an additional unit of rental housing to a neighborhood or increasing the share of rentals as a percentage of the neighborhood's total housing units is found to reduce SF home values by nontrivial amounts. However, the magnitudes of the reduction in home values vary across different types of rentals. The negative house value impacts of SF and mobile home rentals are roughly four times larger than rentals found within condominiums. A typically sized MF property containing apartment rentals has a negative effect on house value comparable to that of a SF or mobile home rental.

As they stand, my results have limited policy implications. What they show is that rentals produce negative externalities that matter to neighborhood property values. As such, they point to the need for additional research into the various pathways that may account for this finding. This research might be productively guided by the following expectations. Which of the hypothetical mechanisms would be most relevant to SF rentals, compared to apartments or condominiums? External maintenance seems like a plausible difference - MF buildings generally have property managers, landscapers, and maintenance staff to keep up the building, but SF rentals may either assign these tasks to tenants or landlords, which likely leads to greater variation in maintenance levels. On the other hand, in comparison to SF rentals, the physical dimensions of MF buildings are more out of character with the rest of the neighborhood and may increase automobile congestion. Regarding a possible crime linkage, the expectation is that the residents of MF rentals have lower incomes than SF rental residents, resulting in the former group having a lower opportunity cost of committing crimes within the neighborhood. These expectations suggest that the pathways whereby rentals reduce SF home values are unlikely uniform and may vary across different types of rentals. The hope is to find the source of the negative spillover effects produced by rental housing and reduce or eliminate them with appropriate policy interventions that do not exclude rentals from SF neighborhoods.[13] In previous research (Ihlanfeldt and Yang, 2019) we have found that rentals help integrate neighborhoods both racially and socially; hence, they should remain a housing option within most neighborhoods.

[13] Some possible interventions might be natural buffers between MF and SF housing, stepped up law enforcement where there has been an increase in rentals, and encouraging local governments and homeowner associations to adopt and enforce housing maintenance codes.

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Table 1
FHFA House Price Index: Means and Standard Deviations (SD)
of Census Tracts by Year of Panel

	HPI		*ln* HPI	
	Mean	SD	Mean	SD
2006	373	122	5.87	.33
2007	366	120	5.85	.33
2008	308	102	5.68	.33
2009	244	81	5.44	.32
2010	231	78	5.39	.33
2011	211	79	5.28	.37
2012	204	83	5.24	.39
2013	226	91	5.34	.40
2014	267	107	5.51	.40
2015	296	117	5.61	.39
2016	322	121	5.71	.38
2017	349	125	5.79	.37

Table 2
Census Tract Means and Standard Deviations (SD) of Housing Variables

	Counts		Shares (%)	
	Mean	SD	Mean	SD
Single-family owner				
Total	1209	536	51.5	22.3
LE	569	547	23.6	22.2
ME	640	513	27.9	25.4
Single-family rental				
Total	286	126	11.9	5.6
LE	169	172	6.9	6.7
ME	117	109	5.0	4.4
Condo owner				
Total	410	593	13.2	14.7
LE	338	479	11.0	12.9
ME	72	278	2.2	6.8
Condo rental				
Total	245	378	7.8	8.7
LE	204	288	6.7	7.6
ME	41	190	1.1	3.4
Mobile home owner				
Total	8	60	.3	2.6
Mobile home rental				
Total	4	32	.2	1.4
Apartments				
Total	398	497	15.1	16.8
LE	70	147	2.9	5.7
ME	328	442	12.2	14.5

Notes: LE = less expensive units, as defined in text.
ME = more expensive units, as defined in text.

Table 3
Results from Estimating HPI Equation (1): Housing Units
Measured as Neighborhood Counts, Without LE/ME Breakdown

	OLS		2SLS	
Single-family owner	.0001513***	.0001522***	.0002743***	.000258**
	(.000028)	(.0000257)	(.0000909)	(.0001268)
	[.0161251]	[.0152235]	[.0272675]	[.0259]
Single-family rental	−.0004621***	−.0004857***	−.0016747***	−.0016536***
	(−.0004621)	(.0000823)	(.0004134)	(.0003771)
	[−.047524]	[−.0485556]	[−.1680144]	[−.1650102]
Condo owner	.0000006	−.000009	−.0000595	−.0000658
	(.0000217)	(.0000189)	(.0000396)	(.0000402)
	[.0001073]	[−.0009011]	[−.005798]	[−.0066117]
Condo rental	.0000072	.0000177	−.0005555	−.0005932
	(.0000384)	(.000032)	(.0003537)	(.0004172)
	[.0009048]	[.001768]	[−.0562739]	[−.0589742]
Mobile home owner	−.0002756***	−.0002662***	−.0001039	−.0001545
	(.0001054)	(.0001026)	(.0001176)	(.0001335)
	[−.0278903]	[−.0266172]	[−.0102776]	[−.015461]
Mobile home rental	−.0002082	−.0003266	−.0022274**	−.0018313**
	(.0005867)	(.0006241)	(.0009056)	(.0008509)
	[−.0203728]	[−.0326579]	[−.2232289]	[−.1828652]
Apartment	−.0000197	−.0000254**	−.0000139	−.000024
	(.000013)	(.0000129)	(.0000362)	(.0000382)
	[−.0019189]	[−.0025356]	[−.0013674]	[−.0023907]
Non-residential controls	No	Yes	No	Yes
Observations	4802	4802	4802	4802
Endogeneity test				
Chi-sq (7)			18.946	18.084
p-value			.0084	.0116

Notes: Clustered standard error at the tract level is in parentheses.
Exact percentage change in HPI from a unit change in housing variable is in brackets.
***, ** indicate statistical significance at the 1 and 5 percent levels, respectively.

Table 4
Results from Estimating HPI Equation (1): Housing Units
Measured as Neighborhood Counts, With LE/ME Breakdown

	OLS		2SLS	
Single-family owner				
LE	.0001182***	.0001244***	−.0004144**	−.0005212**
	(.0000278)	(.0000266)	(.0002125)	(.0002535)
	[.0117133]	[.0124414]	[−.0414271]	[−.0521078]
ME	.0000729**	.0000841***	.000014	.0000133
	(.0000296)	(.000026)	(.0003466)	(.000382)
	[.0071043]	[.0084103]	[.001398]	[.0013347]
Single-family rental				
LE	−.0006149***	−.0006421***	−.0027552***	−.0028038***
	(.0000704)	(.0000718)	(.0009161)	(.000993)
	[−.0614876]	[−.064194]	[−.275137]	[−.2799867]
ME	.000309***	.000252**	−.0042659*	−.0046142*
	(.0000994)	(.0000991)	(.0023605)	(.0027108)
	[.0310893]	[.0252068]	[−.4256789]	[−.4603601]
Condo owner				
LE	−.0000189	−.0000246	.0000269	.0000139
	(.0000197)	(.0000172)	(.0001344)	(.0001362)
	[−.0018505]	[−.0024576]	[.0026891]	[.0013934]
ME	.0000063	.0000014	−.0008894***	−.0006736**
	(.0000463)	(.0000405)	(.000307)	(.0002743)
	[.0006262]	[−.0001369]	[−.0889044]	[−.0673332]
Condo rental				
LE	.0000339	.0000473	−.0020926***	−.0023342***
	(.0000446)	(.0000392)	(.0006436)	(.000798)
	[.0032525]	[.004752]	[−.2090376]	[−.2331526]
ME	.0000058	.0000156	−.0013005*	−.0018259
	(.0000632)	(.0000555)	(.0007097)	(.0008676)
	[.0007207]	[.0015595]	[−.129969]	[−.1824222]
Mobile home owner	−.0002056	−.0002166**	−.0003001	−.0003953
	(.0001099)	(.0001062)	(.0003915)	(.0003846)
	[−.020536]	[−.0216604]	[−.0300021]	[−.0395248]
Mobile home rental	−.0002404	−.0002987	−.0040974**	−.0027264
	(.0004876)	(.0005179)	(.0016848)	(.0020953)
	[−.0241646]	[−.0298655]	[−.4088986]	[−.2722716]
Apartment				
LE	−.0001153***	−.0001213***	−.0005554***	−.0005474***
	(.0000335)	(.0000335)	(.000181)	(.0001925)
	[−.0115154]	[−.0121268]	[−.055199]	[−.0547227]
ME	−.0000323***	−.000037***	−.0001089	−.0000915
	(.0000123)	(.0000122)	(.0001374)	(.0001105)
	[−.0032226]	[−.0037022]	[−.010892]	[−.009154)

Non-residential controls	No	Yes	No	Yes
Observations	4802	4802	4802	4802
Endogeneity test				
Chi-sq (12)			108.693	107.906
p-value			.0000	.0000

Notes: LE = less expensive units.
ME = more expensive units.
Clustered standard error at the tract level is in parentheses.
Exact percentage change in HPI from a unit change in housing variable is in brackets.
***, **, * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 5
Results from Estimating HPI Equation (2): Housing Units
Measured as Neighborhood Shares, Without LE/ME Breakdown

	OLS		2SLS	
Single-family rental	−.0074279**	−.0098095***	−.0474562***	−.0646754***
	(.002976)	(.0027026)	(.0167263)	(.0238584)
	[−.7400371]		[−4.634779]	[−6.262834]
Condo owner	−.002053**	−.0027123***	−.0158592***	−.0206629***
	(.0007952)	(.0007522)	(.0044137)	(.0063727)
	[−.2050932]		[−1.573406]	[−2.045092]
Condo rental	−.0028827**	−.0023637*	−.0118425***	−.0157149**
	(.0013749)	(.0012621)	(.0045013)	(.0063096)
	[−.2878526]		[−1.177264]	[−1.559204]
Mobile home owner	−.012855***	−.0145721***	−.0592095***	−.0668059***
	(.0045554)	(.0048454)	(.0112707)	(.0140623)
	[−1.277274]		[−5.749073]	[−6.462323]
Mobile home rental	−.0059145	−.0106231	−.0554198***	−.061922***
	(.0128904)	(.0127654)	(.018228)	(.019406)
	[−.5897076]		[−5.391214]	[−6.004381]
Apartment	−.002967***	−.0032765***	−.0117139***	−.0152802***
	(.0007949)	(.0007682)	(.0027836)	(.0042631)
	[−.2962576]		[−1.164554]	[−1.516408]
Non-residential controls	No	Yes	No	Yes
Observations	4802	4802	4802	4802
Endogeneity test				
Chi-sq (7)			17.826	18.111
p-value			.0067	.0060

Notes: Clustered standard error at tract level is in parentheses.
Exact percentage change in HPI from a unit change in housing variable is in brackets.
***, **, * indicate statistical significance at the 1, 5 and 10 percent levels, respectively.

Table 6
Results from Estimating HPI Equation (2): Housing Units
Measured as Neighborhood Shares, With LE/ME Breakdown

	OLS		2SLS	
Single-family rental				
LE	−.0143594***	−.0142594***	−.0560103***	−.073411***
	(.0024497)	(.0020847)	(.0197807)	(.0258372)
	[−1.425683]	[−1.415825]	[−5.447059]	[7.678121]
ME	.001891	.0015747	.0085038	−.0094215
	(.0024618)	(.0018628)	(.0238388)	(.0292338)
	[.1892754]	[.1575909]	[.8540071]	[−.9377258]
Condo owner				
LE	−.0028583***	−.0028925***	−.0201061***	−.0236648***
	(.0008432)	(.0007671)	(.0056724)	(.0069365)
	[−.2854261]	[−.2888354]	[−1.990533]	[−2.338101]
ME	−.0012985	−.0016463*	−.0096094*	−.0149932**
	(.0009147)	(.0009003)	(.0055962)	(.0064473)
	[−.1297678]	[−.1644924]	[−.9563366]	[−1.488132]
Condo rental				
LE	−.0003448	.0003352	−.011582**	−.0147284**
	(.0013787)	(.0012496)	(.004949)	(.0061257)
	[−.034478]	[.0335246]	[−1.151514]	[−1.462048]
ME	−.0073422***	−.0062252***	.0034289	.003539
	(.0024562)	(.0023401)	(.0098478)	(.0114218)
	[−.7315279]	[−.6205828]	[.343481]	[.3545317]
Mobile home owner	−.0120708**	−.0134324**	−.0384522***	−.0460366***
	(.0050937)	(.0052692)	(.0097092)	(.0116252)
	[−1.199819]	[−1.334263]	[−3.772232]	[−4.499302]
Mobile home rental	−.0058015	−.0086162	−.0416346***	−.0513418***
	(.0114127)	(.0116875)	(.0156783)	(.0174352)
	[−.5784677]	[−.8579159]	[−4.07798]	[−5.004611]
Apartment				
LE	−.0062745***	−.0062656***	−.0128839***	−.015599***
	(.0010788)	(.0116875)	(.0039409)	(.0050292)
	[−.6254883]	[−.6245983]	[−1.280128]	[−1.547794]
ME	−.0028834***	−.0028483***	−.0106642***	−.0133198***
	(.0007009)	(.0006469)	(.0032318)	(.004299)
	[−.2879263]	[−.2844198]	[−1.060749]	[−1.323149]
Non-residential controls	No	Yes	No	Yes
Observations	4802	4802	4802	4802
Endogeneity test				
Chi-sq (12)			61.079	64.220
p-value			.0000	.0000

Notes: LE = less expensive units.

ME = more expensive units.
Clustered standard error at tract level is in parentheses.
Exact percentage change in HPI from a unit change in housing variable is in brackets.
***, **, * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

Appendix Table A.1
2010 Census Tract Means
Comparisons

	In sample	Out of sample
# tracts	457	762
median income	58548	50527
percent black	19.34	18.25
percent white	44.8	40.3
percent Hispanic	35.8	41.4
percent owner-occupied	68.7	59.5
percent high school or more	83.5	82.7
percent college degree or more	28.9	29.1

Appendix Table A.2
First Equation Set: First-stage Diagnostics
Sanderson-Windmeijer Chi-sq and *F* Statistics
Testing for Under-identification and Weak Instruments

	Without LE/ME		With LE/ME	
	Under id Chi-sq (*p*-value)	Weak id *F* (*p*-value)	Under id Chi-sq (*p*-value)	Weak id *F* (*p*-value)
Single-family owner				
ALL	50.01 (.000)	49.72 (.000)		
LE			40.76 (.000)	40.49 (.000)
ME			34.68 (.000)	34.44 (.000)
Single-family rental				
ALL	15.50 (.000)	15.41 (.000)		
LE			17.40	17.28
ME			8.03 (.004)	7.98 (.004)
Condo owner				
ALL	33.57 (.000)	33.38 (.000)		
LE			39.25 (.000)	38.99 (.000)
ME			11.30 (.000)	11.22 (.000)
Condo rental				
ALL	14.41 (.000)	14.33 (.000)		
LE			17.72 (.000)	17.60 (.000)
ME			14.93 (.000)	14.83 (.000)
Mobile home owner	143.33 (.000)	142.51 (.000)	156.31 (.000)	155.26 (.000)
Mobile home rental	14.74 (.000)	14.66 (.000)	24.47 (.000)	24.31 (.000)
Apartment				
ALL	38.07 (.000)	37.86 (.000)		
LE			29.14 (.000)	28.94 (.000)

ME	49.91 (.000)	49.57 (.000)

Appendix Table A.3
Second Equation Set: First-stage Diagnostics
Sanderson-Windmeijer Chi-sq and *F* Statistics
Testing for Under-identification and Weak Instruments

	Without LE/ME		With LE/ME	
	Under id Chi-sq (*p*-value)	Weak id *F* (*p*-value)	Under id Chi-sq (*p*-value)	Weak id *F* (*p*-value)
Single-family rental				
ALL	50.19	24.95		
	(.000)	(.000)		
LE			44.38	22.04
			(.000)	(.000)
ME			35.49	17.63
			(.000)	(.000)
Condo owner				
ALL	39.48	19.63		
	(.000)	(.000)		
LE			37.32	18.54
			(.000)	(.000)
ME			9.33	4.63
			(.009)	(.010)
Condo rental				
ALL	68.19	34.05		
	(.000)	(.000)		
LE			33.08	16.43
			(.000)	(.000)
ME			25.55	12.69
			(.000)	(.000)
Mobile home owner	210.64	104.72	152.50	75.75
	(.000)	(.000)	(.000)	(.000)
Mobile home rental	37.70	18.74	55.65	23.64
	(.000)	(.000)	(.000)	(.000)
Apartment				
ALL	55.49	27.59		
	(.000)	(.000)		
LE			162.37	80.66
			(.000)	(.000)
ME			42.19	20.96
			(.000)	(.000)