Housing tenure and neighborhood crime

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Abstract

Perhaps the most important legacy of the housing market crash that occurred in the last decade is that millions of single-family homes within America's neighborhoods that were once owner-occupied are now rentals, as billions of dollars of private equity have poured into the single-family home rental business. The group most concerned about this change are homeowners who have long feared that rentals will bring crime into their neighborhood. Surprisingly, there is no extant evidence on this issue. We provide evidence on the relationship between changes in neighborhood crime and changes in the shares of a neighborhood's housing stock that are single-family rentals and other types of rentals. Our estimates are based on a panel of Miami-Dade County neighborhoods covering the years 2002–2014 and the use of newly developed Poisson control function estimators. The latter models allow us to control for unobservable heterogeneity across neighborhoods, the possible endogeneity of our housing variables, and the count nature of our crime data. The results show that an increase in the share of a neighborhood's housing units that are single-family rentals causes a modest but important increase in property crime. However, homeowners are generally not the victims of these crimes, experiencing only an increase in thefts from their motor vehicles.

1. Introduction

Perhaps the most important legacy of the housing market crash that occurred in the last decade is that millions of single-family homes within America's neighborhoods that were once owner-occupied are now rentals (SFR), as billions of dollars of private equity have poured into the single-family home rental business.[1, 2] The growth in single-family rentals has altered the tenure composition of many suburban neighborhoods in favor of rentals and away from owner-occupied homes.[3] Clearly, the group most concerned about this change is existing homeowners, who have long viewed rentals as causing a decline in their neighborhood's quality (Fottrell, 2013; Kremer, 2010; Obrinsky and Stein, 2006; Rohe and Stewart, 1996). Surveys of homeowners reveal that their principal complaints about rentals are that they lower the appearance of their neighborhood because they are less well maintained and that they bring crime into the neighborhood (Dewan, 2013; Kremer, 2010; Realtor Magazine, 2013). While extant empirical evidence supports the first complaint (Galster, 1983; Gatzlaff et al., 1998; Harding et al., 2000; Shilling et al., 1991), surprisingly, we were unable to find any theoretical or empirical research by either criminologists or economists that directly focuses on the relationship between neighborhood tenure and neighborhood crime.[4] If homeowners are correct that rental units are a source of neighborhood crime, the increase in these rentals could radically change the level of safety and security found within their

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[1] According to the Census Bureau's American Community Survey (ACS), the number of single-family rentals (SFR) in the U.S. grew by 31 percent in the ten-year period immediately following the housing crisis (2007 to 2016). In net numbers, single-family rentals in the U.S. increased by 3.6 million units in ten years, more than rental apartments, which increased by 3.2 million units. More evidence on the growth of rentals is presented in section 2.

[2] The lion's share of the investment in single-family rentals has originated from institutional investors. For discussions of their role see Smith and Liu (2017) and Mills et al. (2016). The former study documents that the single-family rental share of all rentals in Atlanta went from 25.4 percent before the housing market crash to 31.7 percent after the crash and that this change was largely the result of investments by institutional investors. The latter study concludes that these investors are in for the long haul and do not intend to liquidate their rental holdings anytime soon. This suggests that single-family rentals in neighborhoods are here to stay.

[3] The Urban Institute projects that the growth in SFRs and multifamily rentals will continue to be strong in the foreseeable future because tight mortgage credit and ballooning student loan debt will push households into the rental market (Strochak, 2017).

[4] A large number of studies have found that higher homeownership rates within neighborhoods are associated with higher housing prices (e.g., Coulson and Li, 2013), but it is not clear why this is true. One possibility is that rental housing increases crime and evidence exists that crime lowers housing prices (Ihlanfeldt and Mayock, 2010).

neighborhoods. The purpose of this paper is to provide the first ever empirical evidence on this relationship. Due to their recent unprecedented growth, our primary interest is on the crime effects of single-family rentals; however, we also provide the first ever evidence on the crime effects of condominium rentals and apartments within multifamily units (MF). The crime-generating effects of MF units are especially important to investigate because opposition to MF housing within suburban neighborhoods is typically strong and is partially based on the perception that MF housing makes neighborhoods less safe, but as Obrinsky and Stein (2006) conclude in their review of the literature, there is virtually no empirical evidence on this issue.

The question we empirically address is what happens to the number of different types of crime within a neighborhood as the share of a neighborhood's housing units represented by rentals increases relative to the share of owner-occupied units. For this purpose, we have constructed a unique panel data set at the neighborhood level for the suburban portion of Florida's Miami-Dade County covering the years 2002–2014. For these years we obtained all crime incident reports from the county's Sheriff's Office. Using the address information contained in these reports, we assigned each crime to a neighborhood. The primary source of our housing data, which cover the years 1999–2014, is the standardized property tax rolls that the county is statutorily required to annually submit to the Florida Department of Revenue (FDOR). These records provide a complete count of each type of housing unit located within each of our neighborhoods.

Our empirical methodology is based on the recent development of Poisson control functions, which allowed us to control for time-invariant unobservable heterogeneity across neighborhoods, the possible endogeneity of our housing variables, and the count nature of our crime data. To complete our identification strategy, we follow the recent popularity of Bartik-like instrumental variable construction (Bartik, 1991), where as instruments we predict the share of each type of housing unit for each neighborhood and year, based upon changes occurring in these units at the county level, excluding changes in units located within the home neighborhood.[5] Conceptually, it is hard to reject the strict exogeneity of our instruments and as we document below they are anything but "weak," possessing a strong correlation with our endogenous variables.

2. The Growth in Single-Family Rentals as a Share of the Housing Stock

Just how widespread is the change in tenure in favor of rentals within neighborhoods? It is important to address this question because we wish to show that neighborhood changes in housing tenure within our study area (Miami-Dade County) are not a unique case. In this section we provide evidence for all of Florida and the nation on the change in the tenure composition of neighborhoods and the growth in rentals relative to owner-occupied housing units. While this evidence suggests the shift in favor of rentals and away from owner-occupied housing units may not be a universal phenomenon, it is found within many urban neighborhoods.

In Florida, each county is required to submit a standardized version of its property tax roll to FDOR. These tax roll data, which are updated on an annual basis, contain a wealth of information on real property characteristics, including the type of property (e.g., single-family, condominium), and what is most important for our study is a field that indicates whether or not a property was granted a property tax homestead exemption. According to the Florida Statutes, this exemption is available to "a person who, on January 1st, has the legal title or beneficial title to real property in [Florida] and who in good faith makes the property his or her permanent residence or the permanent residence of another or others legally or naturally dependent upon him or her" [Exemption of Homesteads, 2016]. We 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

[5] The general idea underlying these instruments is that changes within a smaller geographic unit of a larger unit containing the smaller unit are driven by factors within both the smaller and larger units. The former factors may be endogenous to crime occurring within the smaller unit but the factors for the larger unit should not be affected by crime within the smaller unit.

significant tax savings, owner-occupants have strong financial incentives to file for the exemption, and we are thus confident that owner-occupied units will generally be correctly classified based on homestead status. Properties that are not covered by a homestead exemption are primarily either rental units or second homes. The fraction of single-family homes that are second homes is expected to be small because in Florida most vacation homes are condominiums. For condominiums we cannot rule out the possibility that a substantial number of the properties we label as rentals may in fact be second homes not available for rent. However, the location of our neighborhoods within Miami-Dade County suggests that even in the case of condominiums most are rentals and are not second homes.[6]

We use the roll data to show for each of Florida's 67 counties how the tenure composition of the housing stock has changed over time. The stock includes single-family, condominium, and mobile homes (both owner-occupied and rentals) plus the apartments found within multifamily housing. Table 1 shows how all rentals and rentals of different types (single-family, condominium, mobile home, and apartment) as shares of the total number of housing units changed between 2000 and 2014. Our attention is focused on all rentals and the rentals of single-family homes. Based upon the 2010 U.S. Census, counties are divided into 33 urban (denoted with an asterisk) and 34 rural counties.

The first two columns of Table 1 report the overall rental share in 2000 and 2014, while the third and fourth columns report for the same years the single-family rental share. For urban counties the evidence is overwhelming that the shift in favor of rental units, especially those found within the single-family home market, is a widespread phenomenon. With but two exceptions, rentals increased as a

[6] For census tracts the American Community Survey reports the number of vacant units that are for "seasonal, recreational, or occasional use (SRO)." These SRO units most likely fall into the second home group and would be part of what we identify as rentals (i.e., non-homesteaded). For the year 2010 for the tracts in our crime coverage area SROs are on average 1.4 percent of the total number of housing units. For the tracts outside of our coverage area the SRO average percentage is 7.6 percent. We are undercounting the SROs because some may be occupied and not vacant at the time of the survey; however, the large difference in these percentages is evidence that our coverage area is that portion of Miami-Dade County where second homes are less likely to be found. Hence, non-homesteaded properties are more likely to be rentals.

share of the housing stock within all urban counties. On average, the rental share increased six percentage points from 42 percent in 2000 to 48 percent in 2014. With respect to just single-family rentals, without exception, for all of the urban counties there was an increase in share. On average, the single-family rental share increased seven percentage points from 15 percent in 2000 to 22 percent in 2014.

For rural counties, the results are mixed. The rental share and the single-family rental share increased for only 18 counties (53 percent) and 15 counties (44 percent), respectively. These numbers suggest that the changing composition of the housing stock in favor of rentals is primarily an urban phenomenon, but can also be found within selected rural areas.

To further document that the above compositional changes in the housing stock revealed by Florida's property tax rolls are not isolated cases but are happening throughout the state, we used data from the American Community Survey (ACS) to construct Table 2. For the entire state, the rental share of total housing units increased from 30 percent to 36 percent between 2005 and 2014, while the single-family rental share grew from 9 percent to 14 percent over the same period. Note that the ACS data only go back to 2005 and include both urban and rural areas; hence, the share increases are expected to be smaller than those shown in Table 1.

Tables 1 and 2 motivate our analysis of the neighborhood crime effects of rental housing. Urban neighborhoods in Florida are undergoing an important structural change in terms of their housing tenure in favor of rental units, which may have an important impact on levels of neighborhood crime. But what about the nation as a whole? Is there evidence that the rental share is growing at the national level? Again, we turn to the ACS data which allowed us to calculate the all rental and single-family rental shares at the national level. Table 3 shows that between 2005 and 2014 the overall rental share increased from 33 to 37 percent, while the growth in the single-family rental share grew from 10 to 13 percent. Unfortunately, the ACS data did not allow us to break down the numbers in Table 3 into those for urban and rural areas. Based on Table 1, we expect such a breakdown would show much larger rental share increases than those shown in Table 3. Nevertheless, the ACS numbers demonstrate that changes in the tenure composition of neighborhoods in favor of rentals are not just occurring within the state of Florida, but are a nationwide phenomenon.

Another approach toward showing the growing importance of rentals is to calculate their growth over time relative to the growth in owner-occupied housing units. The FDOR tax roll data allowed us to compare growth rates at the county level for Florida. The results are in Table 4. For urban counties the average percentage change in owner-occupied housing units (single-family, condominium, and mobile home) over the 2000 to 2014 time period equaled a modest 23 percent. In contrast, the average change in rental housing units (the above three types of units as rentals plus apartments) was more than twice as great, standing at 66 percent. Most remarkable was the growth in single-family rentals, which surged over 100 percent. At the national level, the ACS allowed a calculation of the growth in owner-occupied and rental housing from 2005 to 2014. The number of owner-occupied housing units actually fell by a small amount, a decline of .44 percent. In contrast, renter-occupied units grew by 17.66 percent. The breakdown by type of rental reveals that single-family rentals grew by a remarkable 36.09 percent, while multifamily rentals increased by 10.34 percent. These numbers for Florida and the nation demonstrate the unpresented growth of rentals, especially single-family rentals, relative to the change that has occurred in owner-occupied housing units.

3. Conceptual framework

How might an increase in the shares of a neighborhood's housing units that are rentals impact neighborhood crime? We draw upon the standard economic model of the rational criminal to analyze these possible effects (Becker, 1968). According to this model the equilibrium amount of crime within a neighborhood occurs where an upward sloping marginal cost (supply) curve of crime intersects a downward sloping marginal benefit curve of crime.[7] Costs (MC) and benefits (MB) are perceived from the criminal's perspective. Because we break our crime counts into categories and the MC and MB curves are expected to vary for different types of crime, the x-axis is not the total number of crimes, but rather the number of a particular crime type. Because neighborhood residents are most concerned about burglary crimes, we define the count of these crimes as our dependent variable, but later consider how our conceptual analysis may differ for other types of crime.

Factors causing shifts in the MC and MB curves alter the equilibrium quantity of crime within the neighborhood. Shifts in the MC curve can come from changes in the criminal's subjective assessment of apprehension and from changes in the direct and opportunity costs of committing a crime. Changes in the expected bounty (loot) from a crime shift the MB curve. Also shifting the MB curve is a change within the neighborhood in the level of "anguish" cost associated with committing a crime. The expected utility from committing a crime is the utility provided by the loot plus the disutility from experiencing guilt following the crime.

Consider how an increase in the neighborhood's housing stock in favor of rental housing might affect the equilibrium number of burglary crimes. At least two factors may result in an increase in the rental share decreasing the probability of apprehension. 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. Therefore, they are less likely to engage in passive policing, whether it be something informal like providing more "eyes on the street" or something more formal such as participating in neighborhood watch programs.

[7] O'Sullivan (2009) presents a simple supply and demand model based on the rational criminal that explains the equilibrium quantity of crime within a city. We draw upon his model in developing an equally simple model to explain the equilibrium quantity of crime within a neighborhood and how this equilibrium may be affected by a change in housing tenure within the neighborhood.

The perceived probability of apprehension within the neighborhood may also decline if rental housing lowers the general physical appearance of the neighborhood. Because rental housing is less well maintained than owner-occupied housing, an increase in the rental share may create negative sight externalities within the neighborhood that make it less visibly attractive. 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.

An increase in the rental share may also lower the MC curve by decreasing the opportunity cost of crimes committed by the neighborhood's own residents. Because of their lower average incomes this cost is lower for renters than for homeowners and criminals tend to commit their crimes within their own neighborhoods (Bernasco and Block, 2011; Pope, 1980; Reppetto, 1974).

Thus far the downward shifts in the MC curve caused by an increase in the rental share of housing suggest that the equilibrium amount of burglary crime will rise in the neighborhood. Turning to shifts in the MB curve, there is one factor from an increase in the rental share that may lower this curve and reinforce the upward shift in the MC curve bringing about a higher equilibrium amount of burglary crime. According to social disorganization theory, the behavior of a neighborhood's residents is affected by the social norms of the neighborhood, which are enforced by existing residents. These norms include an avoidance of crimes against one's own neighbors. Accepting these norms would presumably increase the anguish cost of residents committing crimes within their own neighborhood. Because renters have less social interaction with homeowners than other homeowners, they may be under less pressure to accept the neighborhood's social norms. Hence, an increase in the rental share would lower anguish cost within the neighborhood, shift the MB downward, and raise the equilibrium amount of crime.

Working against all of the above factors suggesting that an increase in the rental share will increase burglaries in the neighborhood, an increase in the rental share may lower expected bounties from crimes committed in the neighborhood, causing the MB curve to move upward and a lower equilibrium amount of crime. In comparison to rental units, owner-occupied units are expected to offer more lucrative crime targets. In large part, this is because homeowners on average are wealthier than renters. Greater wealth results in more expensive household possessions that are attractive to burglars. However, even if both renters and owners are similarly financially endowed, homes occupied by the latter group are generally better targets. Home maintenance requires complimentary goods (e.g., equipment and tools) which are also attractive to burglars and because of their lower mobility homeowners have had more time to accumulate household possessions.

Because an increase in the rental share of housing moves the MC curve downward and has an ambiguous impact on the MB curve, a priori, we cannot attach a sign hypothesis to the effect that an increase in the shares of a neighborhood's housing units that are rentals will have on the equilibrium number of burglaries within the neighborhood. The issue requires an examination of the data.

Exchanging out burglary crimes for one of the other types of crime we analyze makes no difference for the crimes of larceny, robbery, and auto theft. As is true for burglaries, larger neighborhood shares of rentals increase the equilibrium number of each of these crimes by shifting the MC curve downward (by decreasing the probability of apprehension via less passive policing and a decline in the appearance of the neighborhood) and by shifting the MB curve upward (by reducing anguish cost within the neighborhood). Moving the equilibrium amount of these crimes in the opposite direction (downward) results from the MB curve shifting downward due to a decline in the neighborhood's loot. Hence, as for burglaries, a priori, the directional effects of these crimes are indeterminate.

For the crimes of murder and assault the available loot is expected to have little, if any, effect on their MB curves; hence, this offsetting factor for the tendency for crimes to rise in the neighborhood is minimal or nonexistent. The expectation is that an increase in the rental shares will increase the equilibrium number of these crimes within the neighborhood.

A final comment is in order. The strength of the possible shifts in the MC and MB curves from a larger share of rentals outlined above and therefore the change in the equilibrium amount of crime may vary by the type of rental (for example, single-family versus apartments) and the quality of the rental (for example, less versus more expensive). While we do not retrace our above discussion to account for these variances, we do allow for them in estimating our crime models.

4. Data

Our empirical models express crime counts for a neighborhood as a function of the neighborhood's shares of total housing units that are different types of rental housing. To construct our dependent variables, we assigned crimes contained in the incident reports provided by the Miami-Dade County Sheriff's Office to neighborhoods for the years 2002–2014.[8] We chose as our neighborhood unit the census block groups defined for the 2010 census.[9] While census tracts are more commonly used to define neighborhoods, tracts are too large within the suburban portion of the county, especially toward the east approaching the Everglades, to meaningfully represent neighborhoods.[10] Our crime typology consists of property crimes (burglaries, larcenies, and motor vehicle thefts) and violent crimes (robberies, assaults, and murders).

As noted above, the primary source for our housing data is a collection of tax assessment records from the FDOR. These records cover the years 1999–2014. While our crimes only cover the

[8] Our crime data is comprised of more than one million criminal incident reports from unincorporated Miami-Dade County and a collection of suburban jurisdictions that contract with the County for the provision of police services. The jurisdictions are Miami Gardens, Miami Lakes, Doral, Palmetto Bay and Cutler Bay.
[9] Census block groups are contained within census tracts and on average have about 40 census blocks and from 300 to 3000 residents.
[10] Our choice of the census block group rather than the census tract as the unit of observation is also based on Wilson (2015). He experiments with both block groups and tracts as the unit of observation in estimating the crime impacts of foreclosures. He finds that moving from block groups to tracts is indicative of Simpson's Paradox. Simpson's Paradox occurs when a switch to a larger geographical unit alters fundamental relationships between the dependent and independent variables.

years 2002–2014, we use the 2001 FDOR records to define the base year used in constructing our instrumental variables. We also use the FDOR data to obtain counts for each neighborhood/year observation of the following types of commercial establishments—service stations/convenience stores, bars and clubs, stores, and restaurants. These businesses are frequently identified as a source of neighborhood crime and therefore it may be important to control for them in our analysis. Finally, we link the FDOR data to property records from DataQuick that can be used to identify foreclosure completions (i.e., REOs). The algorithm we used to identify REOs with these data is described in detail in our earlier work (Ihlanfeldt and Mayock, 2016). Prior research has shown that there exists a correlation between REOs and neighborhood crime (Ellen and Lacoe, 2015), but whether REOs cause crime has been open to dispute (Jones and Pridemore, 2012; Kirk and Hyra, 2012; Wolff et al., 2014).

Our key explanatory variables are the percentages of the neighborhood's total housing units that are various types of rental housing units. There are three types of rental units—single-family homes, condominiums, and apartments.[11] Two sets of models are estimated. One set uses these percentages as explanatory variables, the other uses percentages where each type of rental unit is divided into less (LE) and more expensive (ME). Any 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. The FMR is set to assure that a sufficient supply of less expensive rental housing is available to program participants. According to HUD, "To accomplish this objective, FMRs must be both high enough to permit a selection of units and neighborhoods and low enough to serve as many low-income families as possible" (HUD, 2007). The FMRs are specific to Miami-Dade County and are reported by HUD for each year of our panel. To make our LE/ME breakdown we first imputed an

[11] Note that mobile homes are excluded from our analysis. Miami-Dade County's land use regulations place strong limits on the number of mobile homes and as a result they are a negligible fraction of the total housing stock.

annual rent for each unit.[12] A unit is designated as LE (ME) if the imputed rent is less than (greater than) HUD's fair market rent (FMR). Our crime coverage area is the unincorporated area of the county. If a block group lies totally within our coverage area, we include it as one of our neighborhoods. This results in 647 neighborhoods (41 percent of the county total), with a total 2010 population of 1,114,943 (44 percent of the county total). The aim in choosing our sample of neighborhoods was to identify suburban neighborhoods where the increase in the share of rental housing poses the greatest crime threat to existing homeowners.

While most of our regressions use the panel defined for the 2002–2014 period, some regressions are run using a shorter panel covering the years 2006–2014. The shorter panel is just the longer panel with the first four years deleted. The shorter panel allowed for the inclusion of demographic variables describing the characteristics of the neighborhood's residents. They come from the ACS which began publishing these data at the block group level in 2006.

Appendix Table A.1 reports the means and standard deviations for crimes and housing shares for selected years of our panel—2002, 2006, 2010, and 2014. Years 2002 and 2014 are the first and last years of our panel. Year 2006 is right before the housing market crashed in Miami-Dade County. Housing values reached near-bottom in 2010 and began to recover in 2011–2012. By 2014 a full recovery was underway (Zillow Home Value Index, 2018).

In light of these housing market dynamics it is not surprising that Table A.1 shows that during the housing market run-up from 2002 to 2006 LE rental shares declined, while ME shares increased for all three types of rentals. In the post-crash period, 2006–2010, just the reverse happened for single-

[12] To calculate an imputed annual rent for each housing unit in our sample, we multiplied an estimate of the rent-to-price ratio by the estimated market value of the property. The rent-to-price ratio is specific to the greater Miami-Dade metro area housing market and is estimated for each year of our 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 Miami-Dade Property Appraiser. 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

family and condominium rentals, with the LE and ME shares increasing and decreasing, respectively. For apartment rentals, both LE and ME shares declined, as apartments overall declined in share. The volatility of these rental share movements over the course of our panel facilitated the identification of their crime effects.

The crime means in Table A.1 show that property crimes within neighborhoods approach an order of magnitude greater than the number of violent crimes for each of the years. Among property crimes, larcenies are, by a wide margin, the most frequently occurring crime. Assaults are the most frequent violent crime, followed by robberies, with homicides being almost nonexistent.

An inspection of the pattern in crimes over our panel shows that without exception all types of crimes declined within neighborhoods. These downward trends in crime within Miami-Dade County are not surprising given the same negative trends in crime at the national level.[13]

5. Methodology

We wish to estimate how a change in the shares of a neighborhood's housing stock represented by different types of rental units impact neighborhood crime. The housing stock consists of three types of rentals—single-family homes, condominiums, and apartments in multifamily housing—single-family REOs, and owner-occupied single-family homes and condominiums. Shares of the housing stock represented by rentals and REOs are included in all of our estimated models, along with neighborhood and year fixed effects. The excluded housing shares are owner-occupied single-family homes and condominiums. Hence, we are estimating how a shift in the housing stock away from owner-occupied units in favor of rentals and REOs affects neighborhood crime. To consistently estimate the crime

[13] Declines in crime might be viewed as inconsistent with a growth in rentals possibly worsening neighborhood crime. This view, of course, is incorrect because all multivariate analysis is based upon the ceteris paribus assumption. More rentals in a neighborhood may cause the decline in crime from national factors to otherwise be smaller in magnitude.

effects of these shifts, three data issues must be addressed. In the literature, handling these issues has come to define an acceptable identification strategy.

First, we measure neighborhood crime as the number of different types of crime that are reported annually in the neighborhood. The distribution of these crime counts is not normal but positively skewed, with a concentration of block group/year observations equaling zero. This non-normality of the distribution violates the use of an OLS model to assess the statistical significance of the explanatory variables and an alternative model, allowing for zero crime counts and skewness, must be found. Second, there may be time-invariant unobservables that are correlated with our housing shares that have their own independent effect on the amount of neighborhood crime. Ignoring these effects may result in biased estimates. For example, criminologists describe a culture of crime that is more or less persistent within certain neighborhoods that results from an absence of social control. Finally, our housing shares may not be exogenous to the number of crimes in the neighborhood. Many examples can illustrate this possibility, which is a concern that radiates throughout the neighborhood crime literature. For example, while a tenure composition shift in favor of rentals may affect the equilibrium amount of crime in a neighborhood, developers of single-family homes may choose to avoid building homes in crime-ridden neighborhoods where their homes may be more difficult to sell. It is also possible that the conversion of single-family homes into rentals by investors may be sensitive to the amount of crime within the neighborhood. Feedback effects from crime to the number and types of housing units that get built or converted from a previous use affect the shares, which violates the assumption of their strict exogeneity and results in inconsistent estimates.

Until recently, addressing all three of these concerns would have been difficult given the econometrician's tool kit of estimators. Fortunately, the recent development of Poisson control functions (PCF) provides an attractive estimation strategy that addresses the count nature of our data, while controlling for neighborhood crime fixed effects as well as the possibility that crime and housing shares within a neighborhood are jointly determined (Wooldridge, 2010, p. 766). In a nutshell, the PCF approach involves the use of a Poisson model to handle the skewed distribution of the data, including time means of the exogenous variables as regressors to control for unobservable time-invariant heterogeneity across neighborhoods, and including as regressors the residuals from reduced form models to control for (and test) the endogeneity of the housing share variables.

The PCF method consists of three steps. First, each of the explanatory variables is regressed on all of the exogenous variables, along with their intertemporal means and year fixed effects. For this purpose pooled (across years) OLS models are estimated. The time means impose the Chamberlain-Mundlak device to control for unobservable time-invariant heterogeneity affecting crime within neighborhoods. As such, there are analogous to including fixed effects in a linear model. In our case, in this step of the analysis the set of exogenous variables (not counting the year variables) and the set of instrumental variables completely overlap. That is, other than the exogenous instrumental variables, there are no other exogenous variables included in the reduced form models. In the second step, the residuals from these estimated models are included as regressors in Poisson models explaining the number of crimes within the neighborhood.[14] A variable is categorized as either endogenous or exogenous based on the statistical significance of the residual attached to the variable in the crime model. If the null hypothesis of exogeneity cannot be rejected at the 10 percent level by a two-tailed test, the share variable is treated as exogenous in the final estimation of the crime model (step three) and its residual is dropped from the model.[15, 16]

[14] The PCF estimator requires that the endogenous variables are continuous and not discrete and can be directly related, with an additive nominal error, to the exogenous variables. Our explanatory variables are percentages and therefore are continuous variables.
[15] Wooldridge (2010, p. 766) notes that the appropriate test statistic is an asymptotic *t*-statistic, robust to arbitrary serial correlation and unspecified variance. Hence, we cluster our standard errors at the block group level.
[16] Testing for the endogeneity of a regressor and treating it as exogenous if the null hypothesis cannot be rejected is important because instrumenting an exogenous variable may result in a significant loss in efficiency.

We estimated both PCF and linear fixed effects (LFE) models. Our estimated models can be divided into three sets, denoted as A, B, and C. In the expression of our estimated equations, an underline under the variable name indicates it is treated as endogenous; a bar, hat, and curl above the variable name denotes the intertemporal mean, the instrumented value, and the residual associated with the reduced form estimation of the variable, respectively. Set A constitutes the simplest of our estimated PCF models and can be expressed as

$$C_{i,t} = exp\ \left(\theta_t + S_{i,t}B_1 + \underline{\tilde{S}}_{i,t}B_2 + \overline{S}_{i,t}B_3 + \underline{\hat{\overline{S}}}_{i,t}B_4\right),$$

where $C_{i,t}$ = the number of crimes reported in neighborhood *i* in year *t*

$S_{i,t}$ = the set of housing shares (single-family, condominium, and apartment rentals plus REOs), measured for neighborhood *i* on January 1 of year *t*

$\underline{\tilde{S}}_{i,t}$ = the residuals from the reduced form models for those explanatory variables treated as endogenous

$\overline{S}$ = the time means of the explanatory variables treated as exogenous

$\underline{\hat{\overline{S}}}$ = the time means of the instruments for the explanatory variables treated as endogenous

θ_t = year fixed effects.

Set B are the LFE models, which can be expressed as

$$C_{i,t} = \lambda_i + \theta_t + \underline{S}_{i,t}\alpha_1 + S_{i,t}\alpha_2 + \varepsilon_{i,t}\ ,$$

where $C_{i,t}$ and θ_t are defined as before, λ_i is a fixed effect for the neighborhood, and

$\underline{S}_{i,t}$ = the set of housing share variables treated as endogenous

$S_{i,t}$ = the set of housing share variables treated as exogenous.

Our interest in estimating the set B models is to see how different the PCF estimates are from those obtained from a LFE model. Therefore, for the sake of comparison, whatever shares are treated as endogenous in the PCF models (after testing) are also treated as endogenous in the LFE models.

Set C models are identical to set A models except that the rental shares are broken down into less (LE) and more (ME) expensive, as defined in section 4.

We needed separate instruments for each of our housing share variables. As is well known, a valid instrument must be highly correlated with the endogenous explanatory variable and uncorrelated with the error term of the crime equation. To construct such variables, we first defined a base year preceding the beginning of our panel. We chose 2001, the year before the start of the panel, as the base year, but as noted below the results are robust to using an earlier year.[17] Using the entire county and not just the suburban area including our neighborhoods, we then calculated the percentage change in the housing share (*S*) at the county level between the base and current years, excluding the home neighborhood values.[18] These percentage changes were then multiplied by the base year value of the share to obtain a prediction of the current year share value ($\hat{S}$), assuming the growth in the share followed the change that occurred at the county level. Formally,

$$\hat{S}_{ijt} = S_{ijb} \times \left(1 + \frac{x-y}{y}\right),$$

where $x = S_{ict}$

$y = S_{icb}$

and *i* indexes the type of rental unit (or REO), *j* indexes the block group, *t* indexes the current year, *b* is the base year (2001), and *c* represents the county. While crime within the neighborhood may affect S_{ijt} it should not have an effect on $\hat{S}_{ijt}$; hence, $\hat{S}_{ijt}$ is exogenous to our crime counts and serves as our instrumental variable.

[17] While we use crimes reported for the years 2002–2014 in constructing our panel, data for the construction of our explanatory variables are available for earlier years, thus allowing our base year to precede the start of our panel.

[18] The use of the entire county (and not just the suburban portion of the county containing our neighborhoods) and excluding the home block group in computing the percentage changes further ensures the exogeneity of our instruments.

Besides $\hat{S}$ satisfying the assumption of strict exogeneity, its validity as an instrument hinges upon its correlation with *S*. While the PCF estimator yields no first-stage diagnostics on the strength of this correlation, these diagnostics are provided from estimating our crime models using two-stage least squares (with block group and year fixed effects). They show that for all of our housing shares $\hat{S}$ and *S* are strongly correlated, with the first-stage *F*-statistic significant at better than the 1% level.[19]

Separate crime models are estimated for property crimes and violent crimes, where the former equals the sum of burglary, motor vehicle theft, and larceny crimes, and the latter equals the sum of robberies, assaults, and murders. Models are also estimated for each of the individual crimes that make up these two aggregates.

6. Results

The results from aggregating crimes into property and violent crimes are reported in Table 5. Tables 6 and 7 show the results from estimating separate equations for each type of property and violent crime, respectively. For each of the estimated PCF models, along with the estimated Poisson coefficient, we report its estimated standard error (clustered at the block group level) in parentheses and its implied average partial effect (APE) in brackets. The estimated Poisson coefficient is a semi-elasticity, showing the percentage change in the number of crimes in response to a unit change in an explanatory variable. Since our share variables are measured as percentages, a unit change equals a one percentage point increase. The APE shows the average change in the number of crimes from a one percentage point increase in a share variable averaged across all of the neighborhoods in our sample (i.e., it is the partial derivative). The APE is analogous to the estimated coefficient obtained from a linear model. For each type of crime, the results are presented in two columns. The first column defines the

[19] We also conducted the Sanderson-Windmeijer tests of underidentification and weak identification, respectively, of individual endogenous regressors. They are constructed by "partialling-out" linear projections of the remaining endogenous regressors. The null hypothesis is that the particular endogenous regressor in question is unidentified. Test results based on robust *F*-statistics indicated that the null could be rejected at better than the 1% level for each of our endogenous variables.

rental shares as single-family homes, condominiums, and apartments. The second column breaks each of these shares into LE and ME.

To overview the results, all three types of rentals—single-family homes, condominiums, and apartments—have positive and statistically significant effects on neighborhood crime. The crime effects of the rentals are found to have their largest impacts on property crimes, especially larcenies and burglaries. While statistically significant, the effects on violent crime are small in comparison. The magnitudes of all of the rental share effects are much more pronounced for single-family and apartment units, in comparison to condominiums. Finally, breaking down the rentals into quality classes (LE and ME) substantially improves the fits of the models and generally yields stronger results.[20]

Columns 1, 2, 4, and 5 of Table 5 present the results from estimating property and violent crime models using both the PCF and LFE estimators, without the LE/ME breakdown. In the property crime models the null hypothesis of exogeneity could not be rejected for any of the housing shares and therefore none of the variables are instrumented. In the violent crime models exogeneity is rejected for multifamily rentals and therefore are instrumented.

A comparison of the results obtained with the PCF and LFE estimators shows that all of the rental share effects that are statistically significant in the PCF models are also significant in the LFE models. Also, with but one exception (the estimated effect of apartments on violent crime), the APEs from the PCF models and the estimated coefficients from the LFE models are similar in magnitude. The similarity between the results obtained from the PCF and LFE models provides some assurance that the

[20] Another general conclusion that can be drawn from the results is that the share of housing units in the neighborhood that are REOs is not found to affect the amount of neighborhood crime. The REO share enters all of our estimated crime models as a control variable and is generally not statistically significant. Where it is significant the size of the effect is small. While this result is inconsistent with the positive findings of some studies (for a review see Ellen and Lacoe, 2015) it is consistent with other studies that find no effect (for a review see Wolff et al., 2014). However, none of the prior studies that have investigated the neighborhood crime effects of REOs have defined the REO variable as a share. Hence, our results are not directly comparable to those in previous studies.

time means in the PCF models are acting like fixed effects, controlling for unobservable heterogeneity in time-invariant factors that may have an effect on neighborhood crime.

Because property and violent crimes are aggregates, there is relatively less clustering at zero (less than one percent for property crime and less than ten percent for violent crime), resulting in an error distribution more closely resembling a normal distribution. This may explain the similarity in the results between the PCF and LFE models. Lending credence to this explanation are the results obtained from estimating the individual crime models. The greater a crime's concentration at zero, the greater the difference between the PCF and LFE estimates.[21] In fact, where there are a large number of observations with zero crimes, as in the case of robbery (35 percent), there is little similarity between the PCF and LFE results. As shown in Table 7, all of the rentals are statistically significant in the robbery PCF model, but none are significant in the LFE model. Also, the estimated APEs are roughly twice as large as the estimated LFE coefficients and for condominium rentals the LFE sign is opposite to the positive sign from the PCF model. These results underscore the importance of using a model, like the Poisson, where the dependent variable takes on only non-negative integer values, with clustering at zero. The wrong functional form can result in badly biased estimates.

While the models without the LE/ME breakdown all show that all three types of rentals have statistically significant effects on neighborhood crime, the models with the breakdown better explain both property and violent crime (see columns 3 and 6 of Table 5).[22] Moreover, the larger magnitudes of the estimated crime effects of the rental shares obtained from the latter models carry considerably greater economic significance. Hence, our discussion of the results focuses on the models containing the LE/ME breakdown (i.e., the set C models described in section 5). Also, because of their easier

[21] The LFE estimates for the individual crime models are not reported in the tables.
[22] Pseudo *r*-squares are larger and Akaike's information criterion statistics are smaller for the PCF models including the LE and ME variables. These statistics are reported at the bottom of each of the tables for both the equations with and without the LE/ME breakdown.

interpretation, the implied APEs, rather than the estimated Poisson coefficients will command our attention.

Focusing first on the property crime results, a one percentage point increase in the share of single-family rentals results in roughly one additional crime based on both the LE and ME APEs. The same share increase for apartments also causes about one additional crime, regardless of expense. The condominium rental effects are not significant.

For violent crime, the estimated effects of the rentals are much smaller in magnitude. While generally significant, the largest change from a one percentage point increase in a rental share is only a .05 increase in crime (single-family, ME). As is true for property crime, an increase in neither the LE nor ME condominium rental share is found to have a significant effect on violent crime.

The results in Table 5 suggest that increasing the shares of single-family and apartment rentals within a neighborhood will raise the level of property crime. This begs the question, which particular property crimes—larcenies vs. motor thefts vs. burglaries—underlie the property crime results.

As is true for the models previously discussed, breaking down the rentals into quality categories (LE and ME) improves the fits of the individual property crime models by nontrivial amounts. Hence, we focus on these results. Perhaps of no surprise, the results presented in Table 6 suggest that larcenies largely account for the effects of LE and ME on property crime. A one percentage point increase in the share of LE or ME single-family rentals results in about .6 and .9 more larceny thefts, respectively. For the apartment rental shares both increases result in about .7 more thefts. LE and ME share increases in single-family and apartment rentals both increase the number of burglaries, but here a one percentage point increase results in only about a quarter of an increase in crime. In other words, the share increase would have to be four percentage points to cause one additional burglary crime. An increase in the condominium rental shares has no effect on larcenies, but raises the number of burglaries by .432 (LE) and .142 (ME). While the size of the ME effect suggests it may not have any economic significance, a two percentage point increase in a LE condominium rental is associated with one additional burglary. Increasing the LE or ME share of any type of rental has little effect on the number of motor vehicle thefts, but the effect is statistically significant in the former case for apartment rentals.

Turning to the estimates obtained from estimating models for the individual violent crimes—robbery, assault, and murder—we would not expect large effects from the rental shares based on the violent crime results presented in Table 5. This is indeed the case; however, there are a number of effects that are statistically significant. Single-family rentals increase robberies (LE) and assaults (ME). Apartment rentals increase assaults (LE and ME) and murders (LE). Condominium rentals increase assaults (ME). Again, in light of the small APEs associated with these effects, a distinction should be drawn between their statistical and economic significance.

To better judge the magnitudes of the estimated rental effects on the individual crimes reported in Tables 6 and 7, we constructed summary Table 8. The question addressed in the table is how many more crimes would there be in a neighborhood if one of the rental shares increased by one standard deviation (SD). With panel data a SD change can be measured as either "between" or "within." The between SD comparison can be thought of as randomly selecting two neighborhoods from the same year, with one experiencing and the other not experiencing a standard deviation increase in the share of a rental. The within SD compares two randomly selected years for the same neighborhood, where in one of the years but not the other there is a standard deviation increase in the rental share. Hence, the two SDs provide alternative ways to gauge the economic significance of the rental effects on neighborhood crime.

In addition to showing the additional crimes of each type that would result from a SD change in a rental share, the final column of Table 8 sums up these changes to obtain the total increase in crime. Also shown is the percentage change in crime that would be experienced by the median neighborhood from the total increase in crime.

The numbers and percentages in the final column of the table suggest that, except for ME condominium rentals, all of the other types of rentals have a meaningful impact on neighborhood crime. Moreover, the magnitudes of the effects seem to be plausible. For our primary interest—single-family rentals—a between SD increase in share causes about a 10 percent increase in neighborhood crime, regardless of the quality of the rental. Similar percentage changes are registered for a within SD increase.

For apartments, a between SD increase in a LE share has an especially large impact on total crime—26 more crimes and a 47 percent increase in crime for the median neighborhood. These large magnitudes are due to the large between SD (21) that reflects the large variance in LE units across the neighborhoods within our suburban sample. A within SD increase produces 9 more crimes and a 16 percent increase, which are changes more in line with the results obtained for single-family rentals. In contrast to the LE results, the ME crime effects are much smaller, with a between SD increase and a within SD increase yielding 1.0 (1.8 percent) and 2.1 (3.8 percent) additional crimes, respectively.

The condominium rental results also show much larger effects for a share increase in LE than ME. Both SD increases result in about 5 more crimes for a LE increase, but less than one additional crime for an increase in ME.

The contrasting crime results for LE and ME share increases for both apartment and condominium rentals indicate that when it comes to multifamily housing, whether the units are apartment or condominium units, it is the less expensive units that are the source of neighborhood crime. As described in section 1, the fear that multifamily housing engenders greater neighborhood crime partially underlies the opposition that suburban homeowners have against this type of housing. Our results suggest that this fear should be conditional on the quality of the rentals.

7. Robustness checks

We conducted a number of robustness checks on our results. First, increasing the share of rentals within a neighborhood may affect the number of crimes in nearby neighborhoods, which may jeopardize the exogeneity of our instrumental variables. We therefore recalculated the county changes in our housing variables used to construct our instruments excluding changes in these variables within the census tract containing the home block group. Second, we experimented with using a base year other than 2001 in calculating the county changes. We tried 2000 and 1999. Moving the base year back in time before the start of the panel further ensures the exogeneity of our instruments. Third, instead of using only block groups that fall totally inside our crime coverage area, we expanded the sample by including block groups whose centroid was within the coverage area. None of these changes materially altered our results.

We also tested the sensitivity of our property crime results from adding in separate models two sets of covariates. One set included the number of four different types of business establishments that are commonly associated with increased crime—shops/stores, restaurants, service stations, and clubs/bars. The other set are demographic variables—the proportions of the population who are males 18 to 24, black, Hispanic, beneath the poverty line, recipients of a high school degree, residents with some college but not a college diploma, and residents with a college or advanced degree. Also included are female heads as a proportion of all household heads. Each of these sets was treated as exogenous because reliable instruments were not available. Also, in the case of the business establishments, the fact that they are count and not continuous variables precludes their treatment as endogenous in the PCF model.

The addition of the business establishments failed to alter the key results reported in any of the tables. Single-family and apartment rental shares remained statistically significant, with only minor changes in the magnitudes of their individual effects. For example, in the case of single-family rentals the LE and ME APEs reported in Table 5 for property crimes are 1.05 and 1.72. After the addition of the business establishments, the APEs are only slightly smaller at .77 and 1.37, with both effects remaining statistically significant at the 5% level.

Adding the demographic variables required reducing the length of the panel by four years, because the ACS first reported these variables for 2006. The ACS does not provide one-year estimates at the block group (BG) level, because there are an insufficient number of survey respondents at this level of geography. Instead, the ACS estimates for BGs are equally weighted averages of responses for the current year and the previous four years. Thus, the estimates are simple moving averages. For example, the estimates reported for 2006 are based on survey responses continuously received over the years 2002–2006. While the use of these estimates will understate year-to-year changes in our demographic variables, they suffice to capture trends in these variables that may be correlated with our housing shares. Moreover, they represent the “best” annual estimates currently available at the block group level.

A comparison of the results with and without the ACS variables allows an assessment, albeit rough, of the possible importance of omitted demographic variables in explaining the estimated crime effects obtained for the rental shares. Increases in the shares of rentals within a neighborhood may bring in new residents who are more prone to committing crimes. That is, what may matter to neighborhood crime is not the change in tenure, per se, but the change in the composition of the population induced by the change in tenure. Re-estimating the property crime model for the years 2006–2014, without the demographic variables, resulted in the single-family and apartment rental shares again achieving statistical significance. The magnitudes of the APEs are larger than those reported in Table 5. The addition of the demographic variables had no discernable effect on these results, which suggests that the omission of demographic controls is not driving the results reported in Table 5. The same conclusion was reached after adding the demographic variables to the individual property crime models—i.e., none of the results reported in Table 6 are materially affected. These results suggest that we are indeed estimating the neighborhood crime effects of a change in the tenure composition of the neighborhood, rather than simply a change in the demographic mix of the neighborhood's residents.

Finally, we investigated the possibility that the crime effects of a change in the composition of the neighborhood's housing stock in favor of rentals and away from owner-occupied housing may depend on the size of the stock. For example, a one percentage point increase in the share of apartments may have a larger effect on crime within a neighborhood with a larger stock because there would be a greater number of new apartments within the neighborhood. In comparison to a linear model, adding variable interactions to a non-linear model is not as straightforward. Our interest is in how the APEs of each of the rental shares change in response to an enlargement in the stock of housing:

$$\frac{\partial\ (\partial y \,|\, \partial x)}{\partial H},$$

where $y =$ # crimes

$x =$ a housing share

$H =$ total number of housing units.

Pinzon (2016) shows how the margins command in Stata can be manipulated to estimate the above derivative. Adapting his code to our case, we estimated the above derivative for each of the LE and ME rental shares in the property crime model of Table 5. With but one exception, the derivative is not significantly different from zero at even the 30% level. The exception is the ME share of apartments (*p*-value = .035), where an increase in *H* is found to increase the APE. However, an additional unit of *H* causes only a 1.17e-09 increase in the APE, a change of no importance.[23]

8. Homeowners as victims

[23] In adding *H* to the estimated equation, both exogenous and instrumental variables were alternatively employed. In both cases, *H* was not found to have an independent effect on crime.

As noted in section 1, homeowners have been particularly virulent in their opposition to rental housing, in part, because of their fear that it will bring more crime into the neighborhood. Thus far we have demonstrated that this fear is not baseless. Our results show that more rentals, whether they be single-family or multifamily units, are associated with an increase in property crimes within the neighborhood. However, a remaining issue is the extent to which homeowners themselves are the victims of these crimes. They could be victims in the sense that higher neighborhood crime lowers their property value, something that we have already shown in previous work (Ihlanfeldt and Mayock, 2010). They could also be victims if the crimes that occur within their neighborhood are perpetrated against their own properties. To investigate this, we wish to shift the focus from neighborhood crime to crime occurring on single-family owner-occupied properties (CSF) within the neighborhood. First, we know that

$$CSF = SSF * CPS,$$

where SSF = share of housing units in the neighborhood that are single-family owner-occupied units ($SFOO$), and CPS = crimes per share of single-family owner-occupied units.

Differentiating with respect to an increase in a rental unit share yields

$$\frac{\partial CSF}{\partial R} = \frac{\partial SSF}{\partial R} * CPS + \frac{\partial CPS}{\partial R} * SSF.$$

The first product accounts for the fact that an increase in the share of a rental will decrease the share of *SFOO* units, which will reduce the number of crimes in the neighborhood occurring on the latter properties. The second product registers the increase in crimes within the neighborhood occurring on *SFOO* from an increase in *R*. The partial derivative in the first product need not be estimated because its value is a −1. By construction, a one percentage point increase in a rental share decreases the single-family share by one percentage point. It is the partial derivative in the second product that we are interested in; namely, how does the number of crimes per share of *SFOO* change with an increase in a rental share.

To investigate this, we assigned the crimes within our neighborhoods to those that occurred on *SFOO* properties. First, we took each of the reported addresses attached to each crime incident report and matched them with an address found within the property tax rolls. Then, using the land use code identifier on the property tax rolls, we summed up the number of each type of crime that occurred on *SFOO* properties. With these data, we ran regressions where the dependent variable equaled *CPS* and the independent variables were the same rental and REO shares entering our neighborhood crime models. Because the dependent variable is a ratio and not a count, in lieu of the PCF model, we estimated linear models with year and neighborhood fixed effects.

Separate equations were estimated for larcenies, burglaries and motor vehicle thefts. Each of the housing shares was tested for endogeneity using a Hausman test. In all cases, the null hypothesis of exogeneity was rejected only for the REO shares; hence, it was in all cases instrumented.[24] Separate equations were estimated for larcenies, burglaries, and motor vehicle thefts.

The results are presented in Table 9.[25] For each type of crime, the first column lists the results without the LE/ME breakdown and the second column has the results with the LE/ME breakdown. For each housing share variable we report the estimated coefficient, the standard error clustered at the block group level in parentheses, and the magnitude of the effect for a between SD increase in the variable in brackets. Given that the dependent variable is the number of crimes per share of *SFOO* housing, how do we judge the magnitude of the effects? Consider the estimated effect of a one standard deviation increase in SF rentals (7.8 from Table 8) on larceny crimes on *SFOO* properties. The estimated coefficient is .30, so the change in the number of larcenies per unit share of *SFOO* properties equals 2.5. A unit share for the median block group is roughly five *SFOO* homes. So every group of this

[24] The first stage F-statistic equals 18 and all other diagnostics of the instrument are highly favorable.
[25] Note that the number of observations used to estimate these regressions is smaller than what was used to estimate the neighborhood crime models. This reflects the fact that there are some neighborhoods that have a zero *SFOO* share.

size is predicted to experience 2.5 additional larceny crimes every year in response to a one standard deviation increase in SF rentals. The size of this effect is plausible—it is modest but nontrivial. The results with and without the LE/ME breakdown tell roughly the same story, so we will stick with the first column results. Continuing our focus on larceny crimes, in comparison to SF rentals, a one standard deviation increase in apartment and condominium rentals have larger effects on these crimes occurring on *SFOO* properties, largely because for these rentals a SD increase is larger. In the case of apartments there is an increase of 10, while for condominiums the increase is 7.

On the surface, these positive effects of all three type of rentals on larceny crimes occurring on *SFOO* properties is perplexing. There are just so many objects that can be stolen from *SFOO* without breaking into the unit (which then would make the crime a burglary and not a larceny). Larcenies include pickpocketing, purse snatching, shoplifting, thefts from machines (e.g., ATMs or soda machines), theft from buildings (e.g., a bicycle theft), and motor vehicle break-ins. We broke down total larcenies into each of its components and estimated separate models for each component crime. The only crime on *SFOO* properties affected by the rental shares was motor vehicle break-ins, which is what we would probably expect, *a priori.*

Turning to the other two types of property crimes, none of the rentals have a statistically significant effect on burglaries occurring on *SFOO* properties. Regarding motor vehicle thefts, the only type of rentals that impacts the number of these thefts on *SFOO* properties are apartments. A standard deviation increase results in 2.5 additional crimes.

A final result of interest is that the REO share of housing units within the neighborhood has a statistically significant effect on all three types of property crimes that occur on *SFOO* properties. In contract to the positive rental share effects, these effects are all negative. A one standard deviation increase in a REO share results in a 1.8, .5 and .7 reductions in larceny, motor vehicle, and burglary crimes on *SFOO* properties, respectively. An explanation for these results is that the opportunity to commit crimes on REO properties shifts the attention of criminals away from *SFOO* properties. REOs are easier targets with less of chance of apprehension. Many studies investigating the effects of REOs on neighborhood crime have found a positive effect, but none has looked at how REOs might alter the distribution of crimes across different types of properties.

9. Conclusion

This paper was motivated by two concerns. Our primary concern arises from a major transformation that has occurred in many suburban neighborhoods. What were once neighborhoods of single-family owner-occupied homes are now mixed tenure neighborhoods including single-family rentals. Has this transformation in tenure mix affected the safety and security of these neighborhoods? Second, one of reasons homeowners have fought the inclusion of multifamily housing within their neighborhood has been a fear that apartment housing would bring crime into their neighborhood. Is this fear grounded in reality? Neither of our concerns has been empirically addressed within the urban economics literature.

Regarding the first concern, we have shown that crime increases with the share of a neighborhood's housing stock represented by single-family rentals. However, while no crimes are good crimes, our results suggest that the crimes associated with these rentals are not in the category of more serious violent crimes but consist only of property crimes. Moreover, the property crimes tend to be mostly larcenies, rather than the more serious crime of burglaries; and when it comes to the victimization of homeowners, the crimes are only larcenies consisting of thefts from motor vehicles. Here the fix would seem to be straightforward. Any fear of victimization that homeowners might have could easily be ameliorated by protecting their motor vehicles. Thefts from cars can be stopped by locking the car, not leaving valuables in the car, and securing any valuables left in the car (e.g., placing them in the glove box).

Regarding the second concern, we find that apartments also do not worsen violent crime within a neighborhood, but raise all three types of property crime—larcenies, burglaries, and motor vehicle thefts. However, this is only true of less expensive multifamily housing. Regarding homeowner victimization, apartment rentals are associated with an increase in both motor vehicle thefts and thefts from these vehicles. Hence, in comparison to single-family rentals, apartments are found to pose a greater problem for homeowners. However, the policy prescription would seem to be nothing more than encouraging homeowners to protect their motor vehicles by locking the doors and perhaps installing car alarms.

The larger policy concern is the impact that all three types of rental housing have on burglaries in the neighborhood. Our results suggest that while these crimes are not happening on single-family owner-occupied properties, and therefore are not an issue for homeowners, they are serious crimes that merit policy intervention. Besides possibly directing more police resources to neighborhoods with a larger share of rental housing, we have no other policy suggestion.

Drawing upon the economic model of crime, we outlined a number of reasons a shift in housing tenure within neighborhoods away from owner-occupied housing in favor of rentals may raise the level of neighborhood crime. These included a reduction in passive policing, a heightened broken-windows effect, a lower anguish cost, and a change in the demographics of the neighborhood's residents. Our data precluded an investigation of the relative importance of these factors, although we did provide some evidence that the effects we observed were not simply being driven by changes in the demographic makeup of the neighborhood caused by the change in tenure. We encourage future research focusing on the underlying mechanisms accounting for our results.

From a social welfare perspective, a change in the tenure composition of a neighborhood's housing stock in favor of rental housing has both pluses and minuses. On the plus side, we have shown in previous work that a compositional shift in favor of rentals opens up housing opportunities for lower income (Ihlanfeldt and Mayock, forthcoming) and minority families (Ihlanfeldt, forthcoming) within better school zones and decreases levels of housing segregation (Ihlanfeldt and Mayock, 2018). On the negative side, in this paper we have shown that this shift worsens neighborhood crime. However, because the opposition to rentals comes largely from single-family homeowners and we find that their victimization is limited to thefts surrounding their motor vehicles, our hope is that our findings will contribute to less homeowner opposition and more affordable housing within suburban neighborhoods, especially those located within better school zones. As recent research has shown, a better neighborhood can result in both short and long run improvements in the lives of the less fortunate families within our society (Chetty et al., 2016).

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Table 1
Shares of Different Types of Rental Housing Units for the Years 2000 and 2014
for Florida Counties

County	Rental 2000	Rental 2014	SF 2000	SF 2014	Condo 2000	Condo 2014	Mobile 2000	Mobile 2014	MF 2000	MF 2014
Alachua*	49.1	58.7	12.6	14.3	2.2	4.9	1.6	1.6	32.7	37.9
Baker	25.1	29.9	11.9	15.9	0	0	8.9	9.9	4.2	4.1
Bay*	52.3	59.7	21.9	22.4	14.0	19.0	5.2	4.9	11.1	13.4
Bradford	35.6	35.6	21.9	20.2	0	0	8.0	11.0	5.7	4.4
Brevard*	34.9	44.1	14.3	21.3	6.6	9.5	1.7	2.0	12.2	11.3
Broward*	46.0	51.4	9.6	12.9	14.1	19.9	0.3	0.3	22.0	18.3
Calhoun	38.6	31.6	24.4	19.7	0	0	10.9	9.2	3.3	2.7
Charlotte*	40.5	53.2	20.0	28.1	10.7	9.9	4.0	3.3	5.7	11.7
Citrus*	32.1	38.5	15.5	23.2	1.7	1.4	10.8	10.2	4.1	3.7
Clay*	21.3	34.0	12.4	18.7	1.1	2.1	6.2	4.7	1.6	8.5
Collier*	59.0	60.7	11.4	15.0	35.8	34.3	1.2	1.1	10.5	10.3
Columbia	34.2	38.1	15.4	16.8	0	0	8.0	10.8	10.7	10.3
Dade*	53.2	57.0	8.2	9.9	15.7	23.0	0	0	29.2	24.1
DeSoto	49.6	50.3	18.0	18.7	3.2	3.6	16.0	13.3	12.5	14.5
Dixie	60.8	41.9	22.5	17.0	0	2.2	36.7	22.5	1.6	0.1
Duval*	41.6	51.5	14.8	20.6	1.1	4.5	1.4	1.1	24.3	25.3
Escambia*	42.1	48.3	20.4	24.0	3.1	7.1	2.5	2.3	16.1	15.0
Flagler*	33.0	40.0	20.7	28.6	4.6	7.7	2.5	1.4	5.3	2.2
Franklin	60.6	60.8	50.5	48.2	0.4	4.7	5.8	6.9	3.9	0.9
Gadsden	33.6	36.5	22.7	21.0	0	0	5.3	6.6	5.5	8.7
Gilchrist	33.3	31.1	13.5	12.4	0	0	17.5	16.0	2.2	2.7
Glades	59.8	54.1	16.4	15.3	0.6	3.1	38.4	28.6	4.3	7.1
Gulf	54.9	57.4	36.2	41.1	0.6	0.9	16.4	13.6	1.7	1.9
Hamilton	39.0	42.4	22.2	17.5	0	0	9.0	11.6	7.8	13.2
Hardee	46.8	47.4	16.8	18.5	3.0	2.0	14.9	9.7	12.0	17.2
Hendry	51.8	48.5	14.0	16.9	1.1	1.4	18.8	18.1	17.9	12.0
Hernando*	27.9	40.3	15.9	27.4	0.6	0.5	7.0	7.3	4.4	5.1
Highlands	41.8	46.3	23.2	28.7	2.2	2.2	7.9	7.0	8.3	8.4
Hillsborough*	39.8	49.2	12.4	19.2	2.6	6.0	1.2	1.1	23.5	22.8
Holmes	35.5	34.5	25.0	27.3	0	0	8.7	9.7	1.8	2.5
Indian River*	41.0	46.3	17.9	23.5	13.2	14.1	1.0	1.0	8.8	7.7
Jackson	39.0	36.9	26.6	24.8	0	0	6.0	7.0	6.4	5.1
Jefferson	41.8	37.2	22.7	18.4	0	0	11.4	9.6	7.6	9.2
Lafayette	100	38.7	45.4	17.4	0	0	42.8	17.9	11.8	3.4
Lake*	32.5	43.0	15.0	23.9	1.3	1.6	7.9	5.6	8.2	11.9
Lee*	51.7	56.7	16.5	25.0	15.9	17.6	3.8	3.0	15.4	11.0
Leon*	43.9	52.8	16.3	18.8	0.6	3.4	2.0	2.4	25.0	28.3
Levy	44.5	39.1	14.8	13.6	1.6	1.3	23.7	20.5	4.4	3.7
Liberty	47.6	41.3	34.0	19.2	0	0	13.0	13.2	0.4	8.9
Madison	41.1	41.3	24.7	20.1	0	0	6.9	8.6	9.5	12.6
Manatee*	48.4	51.4	11.2	19.9	9.9	14.1	4.2	1.9	23.1	15.6
Marion*	36.0	42.9	15.5	22.7	2.3	1.1	9.5	7.8	8.7	11.2

Martin*	39.1	41.5	16.2	17.9	11.6	13.2	2.0	2.0	9.4	8.4
Monroe	65.7	67.5	27.4	30.2	14.4	13.0	7.9	8.0	20.9	16.2
Nassau	37.4	41.7	13.3	19.5	10.5	10.0	4.5	6.7	9.0	5.5
Okaloosa*	45.1	51.6	21.5	26.0	12.5	13.7	1.5	1.0	9.6	10.3
Okeechobee	47.7	51.2	14.7	17.4	0.9	0.8	28.0	25.0	9.1	8.0
Orange*	50.2	55.7	13.8	20.9	6.1	9.0	0.6	0.5	29.8	25.2
Osceola*	48.9	57.7	24.8	33.2	4.7	10.3	2.8	2.2	16.6	12.0
Palm Beach*	45.9	49.5	7.7	17.3	22.2	18.8	0.4	0.4	15.4	13.1
Pasco*	32.2	45.1	15.7	24.8	3.8	3.6	9.2	7.3	3.5	9.4
Pinellas*	43.6	48.5	11.1	15.5	10.3	14.1	1.5	5.2	20.8	16.6
Polk*	44.9	48.9	17.0	25.3	2.7	2.0	7.5	6.2	17.7	14.7
Putnam	42.8	43.7	16.2	17.6	0.4	0.5	21.1	20.6	5.1	5.0
St. Johns*	43.5	37.9	12.5	19.7	9.8	12.0	3.2	2.7	18.0	3.5
St. Lucie*	40.5	45.0	19.6	27.1	9.6	8.2	2.3	2.0	9.0	7.6
Santa Rosa*	35.0	34.5	17.7	21.5	2.4	2.4	7.5	4.5	7.4	6.1
Sarasota*	41.7	49.6	14.8	22.0	15.2	15.2	2.7	3.2	8.9	9.2
Seminole	34.8	45.4	12.9	19.5	2.6	6.5	0.5	0.4	18.7	18.9
Sumter	37.5	32.9	17.9	26.2	0.3	0.4	13.0	4.5	6.4	1.8
Suwannee	31.6	34.5	15.7	15.9	0	0	9.9	16.9	5.9	1.7
Taylor	59.2	46.5	32.5	24.3	0.2	0.1	26.0	16.3	0.5	5.0
Union	41.7	29.4	17.1	11.3	0	0	20.5	13.4	4.1	4.0
Volusia*	41.7	45.8	14.5	24.1	7.5	9.7	1.4	1.5	18.3	10.5
Wakulla	38.7	35.0	20.1	19.1	0.9	2.1	16.1	11.8	1.4	2.0
Walton	66.5	68.7	23.5	33.3	32.3	24.7	7.6	5.9	3.1	4.8
Washington	41.6	39.8	24.4	22.0	0	0	14.6	13.9	2.6	4.0

Notes: Rental shares are calculated as a percentage of the total number of housing units within the county. This total includes all types of rentals and owner-occupied single-family, condominium, and mobile homes.
* indicates the county is an urban county according to the 2010 U.S. Census.

Table 2
Florida Housing Characteristics

	2005	2010	2014
Housing Units	7,048,800	7,035,068	7,328,046
Rental Units	2,144,851	2,240,938	2,634,225
Percent Rental	30.4	31.8	35.9
SF Units	4,454,842	4,600,954	4,726,590
SF Rentals	658,469	795,533	993,103
SF Rentals / SF Units	14.8	17.3	21.0
SF Rentals / All Rentals	30.7	35.5	37.7
SF Rentals / All Units	9.3	11.3	13.5
MF Rentals	1,349,111	1,306,467	1,477,800
MF Rentals / All Units	19.1	18.6	20.2
Percent Change SF Rentals		20.8	50.8
Percent Change MF Rentals		−3.2	9.5

Source: Authors' calculations based on data from the American Community Survey, One-Year Estimates.

Table 3
United States Housing Characteristics

	2005	2010	2014
Housing Units	111,090,617	114,567,419	117,259,427
Rental Units	36,771,635	39,694,047	43,267,432
Percent Rental	33.1	34.6	36.9
SF Units	76,097,073	79,051,519	80,439,967
SF Rentals	11,325,664	13,294,156	15,186,869
SF Rentals / SF Units	14.9	16.8	18.9
SF Rentals / All Rentals	30.8	33.5	35.1
SF Rentals / All Units	10.2	11.6	12.9
MF Rentals	23,644,161	24,491,227	26,090,261
MF Rentals / All Units	21.3	21.4	22.2
Percent Change SF Rentals		17.4	34.1
Percent Change MF Rentals		3.6	10.3

Source: Authors' calculations based on data from the American Community Survey, One-Year Estimates.

Table 4
Percentage Changes (2000 to 2014) in the Number of
Different Types of Housing Units for Florida Counties

County	Owner-occupied	All Rentals	SF Rentals	Condo Rentals	Mobile Rentals	MF Rentals
Alachua*	18.9	74.9	66.9	222.0	48.5	69.3
Baker	63.5	107.8	133.3	0	93.0	67.2
Bay*	21.8	64.4	42.0	96.4	35.0	72.5
Bradford	45.4	45.8	34.5	0	101.0	11.2
Brevard*	13.2	66.7	96.0	90.9	56.7	21.8
Broward*	3.6	28.6	54.5	62.7	11.4	−4.2
Calhoun	72.6	26.8	24.8	0	30.4	28.5
Charlotte*	7.4	79.4	91.3	27.3	14.0	180.9
Citrus*	57.0	68.5	109.7	20.7	32.8	25.6
Clay*	42.0	169.6	155.8	238.5	28.0	778.5
Collier*	38.4	48.7	90.0	38.5	27.0	41.0
Columbia	46.4	72.7	70.0	42.1	110.5	49.0
Dade*	8.2	26.5	41.5	72.6	0	−2.5
DeSoto	23.7	26.9	30.8	42.0	5.0	45.5
Dixie	155.7	18.9	30.5	0	6.0	−87.4
Duval*	14.4	70.3	91.4	468.6	11.1	43.2
Escambia*	14.0	46.6	50.0	188.7	19.5	18.6
Flagler*	79.1	440.9	176.0	234.1	14.5	−15.8
Franklin	36.7	37.4	30.6	1400.0	64.3	−66.5
Gadsden	55.7	73.0	48.2	0	97.1	152.1
Gilchrist	68.4	52.3	49.0	0	49.2	98.8
Glades	23.5	−2.2	0.5	471.0	−19.6	77.5
Gulf	32.7	46.5	58.9	120.1	16.1	51.4
Hamilton	52.8	76.1	28.2	0	109.5	173.7
Hardee	27.2	30.7	41.8	−12.9	−16.3	84.6
Hendry	29.2	12.9	45.5	50.0	16.5	−18.7
Hernando*	10.6	92.8	130.8	14.8	37.8	54.5
Highlands	18.0	41.9	57.9	23.7	13.3	29.4
Hillsborough*	19.5	75.6	119.3	226.9	35.6	37.7
Holmes	53.8	46.9	34.8	0	69.2	106.1
Indian River*	30.6	62.4	88.7	53.4	36.1	75.8
Jackson	52.0	38.7	37.0	0	70.3	16.4
Jefferson	88.9	55.3	41.4	0	46.2	110.6
Lafayette	0	65.4	63.9	0	78.9	22.7
Lake*	36.9	114.9	157.7	92.2	15.9	135.1
Lee*	37.7	68.4	133.3	69.3	21.1	9.9
Leon*	8.4	55.1	48.3	666.8	53.6	45.7
Levy	68.8	35.2	41.3	31.4	32.7	29.8
Liberty	95.2	51.3	−1.7	0	76.9	3066.1
Madison	52.5	53.3	24.4	0	90.6	100.9
Manatee*	22.3	38.0	130.9	84.7	−42.3	−12.2
Marion*	40.8	87.8	130.3	−22.1	30.5	103.7

Martin*	16.0	28.1	33.5	37.5	24.1	8.0
Monroe	−3.1	4.8	37.7	−7.5	3.9	−21.3
Nassau	47.2	76.8	132.1	51.2	133.9	−3.7
Okaloosa*	16.4	50.6	59.5	44.8	37.0	40.7
Okeechobee	16.4	34.1	47.3	19.2	11.3	146.5
Orange*	22.6	53.0	109.1	104.3	22.7	17.0
Osceola*	55.0	120.6	150.0	310.0	43.2	35.6
Palm Beach*	11.8	29.4	168.7	1.0	8.2	1.5
Pasco*	24.0	114.0	141.8	46.3	21.8	302.9
Pinellas*	−2.8	17.9	48.9	46.4	51.3	−15.0
Polk*	33.0	56.4	113.4	39.3	19.8	19.6
Putnam	31.5	36.4	45.1	71.8	30.7	30.1
St. Johns*	73.8	37.5	148.3	92.4	33.7	−69.2
St. Lucie*	41.4	70.1	111.8	32.0	32.9	29.5
Santa Rosa*	42.1	39.1	71.3	44.5	−15.3	15.8
Sarasota*	10.7	52.3	89.5	27.9	51.9	31.8
Seminole	8.2	68.6	96.0	219.1	5.8	30.4
Sumter	196.6	142.1	304.9	230.7	−3.2	−23.8
Suwannee	51.8	73.3	60.8	0	168.1	−53.2
Taylor	58.7	−4.9	−9.4	625.0	−24.2	993.6
Union	87.6	9.3	2.6	0	1.2	50.0
Volusia*	8.1	27.8	93.2	51.1	21.0	−33.1
Wakulla	77.8	51.4	58.7	264.1	22.3	138.0
Walton	77.9	96.2	168.8	45.3	48.2	192.7
Washington	58.7	47.5	38.5	0	47.0	135.2

* indicates the county is an urban county according to the 2010 U.S. Census.

Table 5
Estimated Effects of a Neighborhood's Housing Shares
on Property and Violent Crime

	Property Crime			Violent Crime		
	Poisson, CF	Linear, FE	Poisson, CF	Poisson, CF	Linear, FE	Poisson, CF
SF [a]	.0021	.1538		.0126***	.0767**	
	(.0016) [b]	(.1256)		(.0034)	(.0335)	
	[.1421] [c]			[.1011]		
SF, LE			.0112**			.0034
			(.0048)			(.0022)
			[.7413]			[.0276]
SF, ME			.0180**			.0058**
			(.0075)			(.0028)
			[1.1898]			[.0469]
APT	.0023**	.2281***		.0074*	.1423**	
	(.0011)	(.0845)		(.0044)	(.0416)	
	[.1534]			[.0594]		
APT, LE			.0108**			.0032**
			(.0045)			(.0014)
			[.7154]			[.0256]
APT, ME			.0112**			.0042**
			(.0052)			(.0021)
			[.7438]			[.0334]
CONDO	−.0020*	−.1887**		.0089***	.0413*	
	(.0011)	(.0960)		(.0025)	(.0248)	
	[−.1337]			[.0720]		
CONDO, LE			.0075			−.0009
			(.0051)			(.0020)
			[.4967]			[−.0075]
CONDO, ME			−.0091			.0030
			(.0124)			(.0026)
			[−.6025]			[.0244]
REO	.0006	.0428	.0040	.0043*	.0349	.0291
	(.0015)	(.1357)	(.0027)	(.0026)	(.0268)	(.0371)
	[.0405]		[.2620]	[.0349]		[.2334]
Year	yes	yes	yes	yes	yes	yes
R^2	.0861	.1626	.1091	.3203	.0751	.4196
AIC	361556	71199	352471	79966	45729	68299
N	8238	8238	8238	8238	8238	8238

[a] SF = single-family rental share
APT = apartment rental share
CONDO = condominium rental share
REO = completed foreclosure share
LE = less expensive
ME = more expensive

[b] Standard error clustered at the block group level is in parentheses.

[c] Average partial effect is in brackets.

Notes: An underline indicates the variable is treated as endogenous.

*, **, *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

Table 6
Estimated Effects of a Neighborhood's Housing Shares
on Individual Property Crimes

	Larceny		Motor Theft		Burglary	
SF [a]	.0006		−.0006		.0094***	
	(.0017) [b]		(.0027)		(.0023)	
	[.0255] [c]		[.0050]		[.1307]	
SF, LE		.0125**		−.0068		.0191***
		(.0061)		(.0268)		(.0050)
		[.5613]		[.0523]		[.2658]
SF, ME		.0201**		−.0198		.0104***
		(.0096)		(.0198)		(.0032)
		[.8984]		[−.1503]		[.1445]
APT	.0019		.0011		.0043***	
	(.0013)		(.0018)		(.0016)	
	[.0870]		[.0084]		[.0602]	
APT, LE		.0134**		.0448**		.0214**
		(.0063)		(.0220)		(.0100)
		[.6001]		[.3401]		[.2975]
APT, ME		.0146**		.0995		.0147
		(.0072)		(.0648)		(.0186)
		[.6524]		[.7555]		[.2048]
CONDO	−.0030**		−.0046***		.0037*	
	(.0012)		(.0015)		(.0020)	
	[−.1366]		[−.0352]		[.0509]	
CONDO, LE		.0098		.0316		.0311***
		(.0066)		(.0200)		(.0120)
		[.4379]		[.2399]		[.4321]
CONDO, ME		−.0202		.0035		.0102***
		(.0149)		(.0038)		(.0032)
		[−.9023]		[.0262]		[.1424]
REO	.0003	.0045	.0024	.0129	.0304**	−.0252*
	(.0018)	(.0034)	(.0024)	(.0178)	(.0146)	(.0135)
	[.0130]	[.2027]	[.0184]	[.0977]	[.4232]	[−.3568]
Year	yes	yes	yes	yes	yes	yes
R^2	.0515	.0805	.1621	.1871	.1301	.1459
AIC	326729	316759	66352	64404	95013	93313
N	8238	8238	8238	8238	8238	8238

[a] SF = single-family rental share
APT = apartment rental share
CONDO = condominium rental share
REO = completed foreclosure share
LE = less expensive
ME = more expensive

[b] Standard error clustered at the block group level is in parentheses.

[c] Average partial effect is in brackets.

Notes: An underline indicates the variable is treated as endogenous.
*, **, *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

Table 7
Estimated Effects of a Neighborhood's Housing Shares
on Individual Violent Crimes

	Robbery		Assault		Murder	
SF [a]	.0144***		.0113***		.0131**	
	(.0038) [b]		(.0033)		(.0066)	
	[.0422] [c]		[.0564]		[.0015]	
SF, LE		.0054*		.0004		.0084
		(.0030)		(.0017)		(.0075)
		[.0158]		[.0023]		[.0009]
SF, ME		.0044		.0052**		−.0060
		(.0037)		(.0025)		(.0128)
		[.0130]		[.0257]		[−.0007]
APT	.0092*		.0056		.0113**	
	(.0053)		(.0045)		(.0049)	
	[.0271]		[.0280]		[.0013]	
APT, LE		.0027		.0023**		.0131***
		(.0021)		(.0012)		(.0050)
		[.0028]		[.0116]		[.0015]
APT, ME		.0035		.0036**		.0027
		(.0032)		(.0017)		(.0100)
		[.0101]		[.0182]		[.0003]
CONDO	.0087***		.0089***		.0091	
	(.0028)		(.0024)		(.0060)	
	[.0254]		[.0445]		[.0010]	
CONDO, LE		−.0035		−.0007		.0088
		(.0029)		(.0016)		(.0072)
		[−.0102]		[−.0036]		[.0010]
CONDO, ME		−.0023		.0046**		.0154
		(.0050)		(.0018)		(.0137)
		[−.0068]		[.0229]		[.0017]
REO	.0045**	.0645	.0044	.0032	−.1390	−.2400**
	(.0021)	(.0513)	(.0031)	(.0031)	(.0853)	(.1105)
	[.0133]	[.1889]	[.0220]	[.0157]	[−.0157]	[−.0272]
Year	yes	yes	yes	yes	yes	yes
R^2	.2131	.3239	.2863	.3612	.1342	.1555
AIC	47277	41849	56423	50520	5417	5297
N	8238	8238	8238	8238	8238	8238

[a] SF = single-family rental share
APT = apartment rental share
CONDO = condominium rental share
REO = completed foreclosure share
LE = less expensive
ME = more expensive

[b] Standard error clustered at the block group level is in parentheses.

[c] Average partial effect is in brackets.

Notes: An underline indicates the variable is treated as endogenous.
*, **, *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

Table 8
Estimated Crime Effects of
a Between and Within Standard Deviation Change in the Rental Share

	Larceny	Burglary	Motor Theft	Robbery	Assault	Murder	Total [a]
SF, LE [b]							
Between SD (7.8)	4.7	2.1	NS [c]	0.1	NS	NS	6.9 / 12.5%
Within SD (4.4)	2.6	1.2	NS	0.1	NS	NS	3.9 / 7.1%
SF, ME							
Between SD (5.4)	4.9	0.8	NS	NS	0.1	NS	5.8 / 10.5%
Within SD (3.9)	3.5	0.9	NS	NS	0.1	NS	4.5 / 8.2%
APT, LE							
Between SD (21)	12.6	6.2	7.1	NS	0.2	0.0	26.1 / 47.5%
Within SD (7)	4.2	2.1	2.4	NS	0.1	0.0	8.8 / 16.0%
APT, ME							
Between SD (1.5)	1.0	NS	NS	NS	0.0	NS	1.0 / 1.8%
Within SD (3.1)	2.0	NS	NS	NS	0.1	NS	2.1 / 3.8%
CONDO, LE							
Between SD (14.7)	NS	6.3	NS	NS	NS	NS	6.3 / 11.5%
Within SD (6.8)	NS	2.9	NS	NS	NS	NS	2.9 / 5.3%
CONDO, ME							
Between SD (3.7)	NS	0.5	NS	NS	0.1	NS	0.6 / 1.1%
Within SD (4.1)	NS	0.6	NS	NS	0.1	NS	0.7 / 1.3%

[a] The percentage after the slash is the percentage change in crime for the median county given the total increase in crime.

[b] SF = single-family rental share
APT = apartment rental share
CONDO = condominium rental share
LE = less expensive
ME = more expensive

[c] NS = estimated effect is not statistically significant.

Table 9
Estimated Effects of a Neighborhood's Housing Shares on Property Crimes
Occurring on Single-Family Owner-Occupied Properties

	Larceny		Motor Theft		Burglary	
SF [a]	.2894*		.1704		−.0063	
	(.1618) [b]		(.1444)		(.1753)	
	[2.49] [c]		[1.46]		[.05]	
SF, LE		.2968*		.1580		−.0326
		(.1704)		(.1487)		(.1776)
		[2.31]		[1.23]		[−.25]
SF, ME		.3656		.1744		−.0983
		(.2017)		(.1691)		(.2259)
		[1.97]		[.94]		[−.53]
APT	.4645***		.1155**		−.1410	
	(.1775)		(.0600)		(.2046)	
	[10.17]		[2.53]		[−3.09]	
APT, LE		.4522**		.1181**		−.1563
		(.1809)		(.0614)		(.2108)
		[9.50]		[2.50]		[−3.28]
APT, ME		.2101		.1700*		−.3343
		(.2315)		(.0982)		(.3196)
		[.31]		[.25]		[−.50]
CONDO	.4265*		.0438		−.0062	
	(.2634)		(.0622)		(.1534)	
	[6.82]		[.70]		[.10]	
CONDO, LE		.4036		.0531		.0187
		(.2569)		(.0581)		(.1558)
		[5.9]		[.78]		[.27]
CONDO, ME		.6268		−.0105		−.2973
		(.3753)		(.1445)		(.2369)
		[2.3]		[−.04]		[−1.10]
REO	−1.2292***	−1.2124***	−.3227*	−.3283*	−.4765**	−.4811**
	(.3625)	(.3667)	(.1847)	(.1856)	(.2052)	(.2031)
	[−1.83]	[−1.82]	[−.48]	[−.49]	[−.71]	[−.72]
FE, Year	yes	yes	yes	yes	yes	yes
FE, BG	yes	yes	yes	yes	yes	yes
AIC	71073	71076	60357	60363	69135	69137
N	6844	6844	6844	6844	6844	6844

[a] SF = single-family rental share
APT = apartment rental share
CONDO = condominium rental share
REO = completed foreclosure share
LE = less expensive
ME = more expensive

[b] Standard error clustered at the block group level is in parentheses.

[c] Change in number of crimes per unit share of rental or REO.

Notes: *, **, *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

Appendix Table A.1
Means and Standard Deviations of Housing Shares and Crimes
for Selected Years of the Panel

	2002	2006	2010	2014
Rental Shares				
Single-Family	10.31	9.53	12.39	13.63
	(11.38)	(8.86)	(9.11)	(9.93)
LE	6.82	3.08	7.38	5.77
	(10.69)	(6.90)	(9.15)	(9.82)
ME	3.49	6.45	5.00	7.86
	(5.94)	(6.61)	(5.18)	(7.36)
Apartments	15.13	13.50	12.66	13.14
	(24.70)	(23.19)	(22.34)	(22.60)
LE	14.91	13.06	12.33	12.63
	(24.54)	(22.97)	(22.25)	(22.40)
ME	0.22	0.44	0.33	0.51
	(3.36)	(1.71)	(1.26)	(1.91)
Condominiums	10.90	13.82	11.20	12.78
	(15.17)	(17.73)	(16.55)	(18.58)
LE	10.21	9.92	10.76	10.99
	(14.78)	(15.54)	(16.12)	(17.51)
ME	0.70	3.90	0.43	1.79
	(2.39)	(7.26)	(2.26)	(5.64)
REO Shares	0.79	0.13	0.39	0.33
	(5.24)	(0.26)	(0.51)	(0.49)
Crimes				
Property	75.60	67.86	61.70	53.44
	(80.53)	(68.59)	(63.47)	(67.58)
Larceny	48.86	43.61	42.44	39.49
	(68.73)	(57.32)	(55.33)	(61.83)
Motor Theft	11.08	9.33	5.70	4.03
	(11.10)	(8.35)	(5.16)	(4.00)
Burglary	15.65	14.92	13.55	9.91
	(11.91)	(13.38)	(13.00)	(11.22)
Violent	9.52	8.68	6.99	6.27
	(13.66)	(12.39)	(10.39)	(10.21)
Robbery	3.23	3.10	2.41	2.40
	(5.68)	(5.16)	(4.16)	(4.44)
Assault	6.18	5.46	4.47	3.76
	(8.71)	(7.84)	(6.53)	(6.10)
Murder	0.10	0.11	0.11	0.11
	(0.36)	(0.42)	(0.42)	(0.42)