Title
The Effect of the Physical Environment on Crime Rates: Capturing Housing Age and Housing Type at Varying Spatial Scales

Journal
Crime & Delinquency, 65(11)

ISSN
0011-1287

Authors
Hipp, John R
Kim, Young-An
Kane, Kevin

Publication Date
2019-10-01

DOI
10.1177/0011128718779569

Peer reviewed

The effect of the physical environment on crime rates:
Capturing housing age and housing type at varying spatial scales

John R. Hipp*

Young-An Kim

Kevin Kane

May 4, 2018

Post-print. Published in Crime & Delinquency 65(11): 1570–1595. 2019

Word count: 6,547

Word count (including references): 8,087

Running Head: "Housing type and crime"

* Department of Criminology, Law and Society and Department of Sociology, University of California, Irvine. Address correspondence to John R. Hipp, Department of Criminology, Law and Society, University of California, Irvine, 3311 Social Ecology II, Irvine, CA 92697; email: john.hipp@UCI.edu. This research is supported in part by NIJ grant 2012-R2-CX-0010

The effect of the physical environment on crime rates:

Capturing housing age and housing type at varying spatial scales

Abstract

This study introduces filtering theory from housing economics to criminology and measures the age of housing as a proxy for deterioration and physical disorder. Using data for Los Angeles County in 2009-11, negative binomial regression models are estimated and find that street segments with older housing have higher levels of all six crime types tested. Street segments with more housing age diversity have higher levels of all crime types, whereas housing age diversity in the surrounding ½ mile area is associated with lower levels of crime. Street segments with detached single family units generally had less crime compared to other types of housing. Large apartment complexes (5 or more units) generally have more crime than small apartment complexes and duplexes.

Keywords: neighborhoods; crime; housing characteristics; housing age.

Bio

John R. Hipp is a Professor in the departments of Criminology, Law and Society, and Sociology, at the University of California Irvine. His research interests focus on how neighborhoods change over time, how that change both affects and is affected by neighborhood crime, and the role networks and institutions play in that change. He approaches these questions using quantitative methods as well as social network analysis. He has published substantive work in such journals as *American Sociological Review*, *Criminology*, *Social Forces*, *Social Problems, Mobilization, City & Community, Urban Studies* and *Journal of Urban Affairs*. He has published methodological work in such journals as *Sociological Methodology*, *Psychological Methods*, and *Structural Equation Modeling*.

Young-An Kim is a Ph.D. student in the department of Criminology, Law and Society, at the University of California, Irvine. His research interests focus on crime patterns at micro places, effects of structural characteristics of blocks on crime, and immigration and crime. Beside criminology, he is interested in sociology of health, urban sociology, and quantitative research methods.

Kevin Kane is a Regional Planner in department of Research & Analysis at the Southern California Association of Governments (SCAG). His research focuses on regional demographic projection, the application of spatial methods to urban land use change analysis, and the relationship between future land use changes, transportation demand, and greenhouse gas emissions. He has published in geographical research in *the Professional Geographer*, *Applied Geographer,* and *Urban Studies,* and planning research in *Landscape and Urban Planning, Environment and Planning A,* and *the Journal of Planning Education and Research.*

The effect of the physical environment on crime rates:

Capturing housing age and housing type at varying spatial scales

A large body of research has focused on the question of where crime is more likely to occur. Whereas some research has shown the importance of the social environment in areas for understanding the location of crime (Sampson and Groves 1989; Weisburd, Groff, and Yang 2012), a body of literature has also demonstrated that certain physical features of the environment are important (Steenbeek, Völker, Flap, and Oort 2012)(Taylor 1996). This research focused on the level of physical disorder in an area (Gault and Silver 2008; O'Brien and Sampson 2015), and the presence of crime attractors such as liquor stores, bars, fringe banks, or marijuana dispensaries (Contreras 2016; Groff and Lockwood 2014; Kubrin and Hipp 2016; Roncek and Maier 1991), or vacant housing units (Cui and Walsh 2015). Much of this literature has invoked the insights of crime pattern and routine activities theories in arguing that certain physical locations can bring about the confluence of offenders and suitable targets (Brantingham and Brantingham 2008; Cohen and Felson 1979). This existing literature has shown the importance of these various features of the physical environment for understanding the location of crime incidents (Chang 2011; Patino, Duque, Pardo-Pascual, and Ruiz 2014).

We extend this literature here by focusing on characteristics of housing, and how they might impact levels of crime. We focus on two specific features of housing. First, we focus on the *types* of housing in a location. Specifically, building on previous research, we expect that detached single family housing will provide different crime opportunities compared to attached single family housing, apartment units of various sizes, duplexes, or mobile homes (Kinney, Brantingham, Wuschke, Kirk, and Brantingham 2008). Given that these different housing types typically are characterized by different street layouts, it is reasonable to presume that they will differentially impact the location of various types of crime (Felson 2002; Patino, Duque, Pardo-Pascual, and Ruiz 2014). This would likely occur given that housing types can impact offenders' perceptions of opportunities in the environment and enhance the possibility of certain types of crime. Second, we extend filtering theory from housing economics to the criminology literature and propose that the *age of housing* will impact the location of crime. Specifically, filtering theory proposes that housing slowly deteriorates as it ages, which reduces its value and results in a transfer of the housing to lower income residents over time (Coulson and Bond 1990; Hoyt 1933; Rosenthal 2014). As a consequence we would expect that older housing will exhibit more deterioration, and hence physical disorder, compared to newer housing. The expected consequence would be higher levels of crime in locations with older housing, although we are not aware of any tests of this in the literature. We will test this here. Relatedly, the mix of housing ages may impact the level of crime at locations (Jacobs 1961; King 2013). Third, we will explore the spatial scale at which these effects of housing type and housing age might operate. On the one hand, we might expect a particularly micro effect at the level of the street segment in which the presence of certain types of housing, or older vintage housing, will lead to higher levels of crime on the street segment itself. On the other hand, the broader spatial pattern of housing types and housing age in the area surrounding a street segment might impact the spatial location of crime incidents. We test these possibilities here, while controlling for the usual predictors of crime at micro-locations.

Literature Review

Housing types and crime: The role of Crime Pattern Theory

In crime pattern theory as put forth by the Brantinghams, the activity backcloth of the spatial layout of physical features can impact the spatial patterns of offenders, targets and guardians, and hence impact the location of crime (Brantingham and Brantingham 1993). Offenders are attracted to areas in the environment that provide more perceived crime opportunities. Whereas many studies have assessed whether certain types of "risky facilities" attract offenders and hence have more crime (Bowers 2014; Deryol, Wilcox, Logan, and Wooldredge 2016), we here focus on the idea of an activity backcloth (Brantingham and Brantingham 1993) and assess whether the type of housing in an area can impact the perception of the presence of suitable guardians and attractive targets. The differing physical layouts of streets with detached single family housing units compared to those with other types of housing—e.g., duplexes—can affect the perception of opportunities for crime or the presence of guardians. Likewise, the physical environments of small or large apartment buildings, or even mobile homes, are different yet, possibly yielding different opportunities for crime.

The presence of different housing types may provide varying opportunities for different types of crime, and therefore be associated with higher or lower levels of crime (Felson 2002). For example, evidence shows that motor vehicle thefts are least likely to occur when autos are parked inside personal garages that are locked (Felson 2002). The implication is that motor vehicle thefts should be least likely to occur in areas with many detached single family homes, but more likely to occur in locations with other types of housing that do not necessarily provide personal garages (i.e., garages are less likely for duplexes or apartment buildings or mobile home parks). For burglaries, the presence of sightlines are posited to increase the ability for guardianship, which would then reduce levels of crime (Felson 2002; Newman 1972). Whereas the specific characteristics of housing arguably are most important for determining such guardianship opportunities, it nonetheless should be the case that general classes of housing will also be important. In small apartment buildings, the limited presence of "eyes on the street" may increase the opportunities for burglaries. In contrast, apartments with many units have high density which would be expected to provide the most visibility and therefore the lowest levels of burglary.

Street robberies are more likely to be suppressed in locations in which there are more "eyes on the street". For example, mobile home parks are often characterized by relatively high density due to the closeness of units, as well as a tendency for outdoor activity given the relatively small interior space (Barthe, Leone, and Stitt 2014; McCarty and Hepworth 2013). A consequence may be considerable eyes on the street, which would reduce the possibility of robberies. In contrast, apartment units typically have more limited view of the street compared to detached single family units, and therefore would be expected to have higher robbery rates. Furthermore, there may be a distinction between single apartment buildings and large apartment complexes given the extent to which they provide eyes on the street. Indeed, a study in the Vancouver area focusing on land parcels provided suggestive evidence in that parcels with large apartment structures tended to have more assaults or motor vehicle thefts those with other types of housing (Kinney et al. 2008). Although this study did not control for the size of the parcels—and therefore those with many apartment units would be expected to have more crime—the results are nonetheless suggestive.

Filtering theory and housing age

Whereas different types of housing may provide varying crime opportunities, we argue that housing age can also have important consequences for neighborhood crime. This insight is based on filtering theory, which was developed in housing economics (Hoyt 1933; Lowry 1960) based on the key insight that as housing ages it deteriorates and becomes less desirable (for a nice review, see Baer and Williamson 1988). Thus, as housing ages, the value slowly declines *relatively* (Coulson and Bond 1990; Smith, Rosen, and Fallis 1988). This decline is, of course, quite slow, as housing remains quite viable for a long time. Nonetheless, all housing ages and begins to show signs of wear and tear, necessitating various forms of upkeep and repair. This decline is sometimes masked in areas in which there is general housing price appreciation, as it will appear that all housing prices are rising. In these appreciating areas the value of the land is rising faster than the value of the housing structure is declining. Empirical evidence has shown that as housing ages the housing price appreciation will be somewhat less than the price of new housing, and therefore will exhibit relatively lower housing prices (Coulson and Bond 1990; Smith, Rosen, and Fallis 1988). A consequence is that over time the residents moving into older housing will have lower household income (Rosenthal 2014). As lower income households move into aging housing, they may be less financially able to perform routine maintenance and there is therefore the risk that the housing will slowly become more dilapidated and exhibit more physical disorder.

A rarely considered consequence of this aging housing is that we would expect such units to exhibit more physical disorder, which criminological theory posits should result in more crime (Skogan 1986; Skogan 1990; Taylor and Covington 1988). Although there is scant research addressing this question, as a simple assessment we used annual American Housing Survey (AHS) data from 1985-92 and computed the relationship between the age of the house and the reported physical disorder in the nearby area by the respondent. We found that for every 10 additional years of housing age, the odds of reporting problematic housing nearby increased 13.8%, and the odds of reporting nearby litter increase 16.3%. And a one standard deviation increase in housing age was associated with a .224 standard deviation increase in the reported level of a physical disorder index. Thus, there is evidence consistent with the idea that older housing will tend to experience more disorder.

Furthermore, theories such as broken windows theory posit that physical disorder can serve as a cue to offenders that residents in a neighborhood are not engaged in the community, and that this lack of engagement results in less guardianship capability which then makes the area a richer crime target given the reduced likelihood of detection for crime events (Wilson and Kelling 1982). Likewise, residents in such neighborhoods may perceive the physical disorder as an indication that their fellow residents are not willing to engage in informal social control, and therefore they themselves are less willing to provide information social control in the community (Ross, Mirowsky, and Pribesh 2002; Taylor 1997). Such neighborhoods would then have less collective efficacy, and therefore be more vulnerable to crime (Sampson, Raudenbush, and Earls 1997). Thus, we argue that older housing can serve as a crude proxy for physical disorder, and would be expected to be associated with higher crime rates. Note that this would be independent of whatever effect the movement of lower income residents into the housing unit might have on crime rates. We highlight that we are aware of no tests of this hypothesis.

At some point in the distant future the aging housing may actually become desirable for gentrification: in such cases, higher income households will move into the unit but will then spend considerable amounts of money to fix and update the housing. There is a long literature describing various gentrification processes (Ellen and O'Regan 2011; Owens 2012; Theodos, Coulton, and Pitingolo 2015) . There is also literature studying how gentrification is related to levels of crime (Barton 2016; Boggess and Hipp 2016; Kreager, Lyons, and Hays 2011; Papachristos, Smith, Scherer, and Fugiero 2011). Note that this literature focuses on the sharp discontinuity of a neighborhood when entering residents engage in renovation to distinctly improve the units, resulting in higher home values. The neighborhood also typically experiences sharp changes in the characteristics of residents based on socio-economic status, and sometimes race/ethnicity (Delmelle 2015; Freeman and Cai 2015; Hwang and Sampson 2014). Thus, filtering theory focuses on how housing slowly becomes more dilapidated—and we focus here on how that may have consequences for crime—but then this decline can be sharply reversed at moments of gentrification.

Mixing building ages: Consequences for crime

Another perspective is that of Jacobs (1961), who argued that it is not simply the *average* age of buildings in a location that is important, but that the *mix* of ages is important. In her perspective, a mix of building ages leads to a mix of activities and hence more vibrancy and activity on the street. This is because various aged buildings can allow for different types of businesses and services given that the rent will differ for older versus newer buildings. A consequence is that there will be more eyes on the street, and hence less crime.

Although Jacobs focused on the age of buildings in general, this idea may extend to the age of housing and was drawn out by King (2013). King pointed out that in planned developments the housing is all built at the same time. A consequence is that such locations will have very little variability in housing age. In contrast, non-planned developments will be built in fits and starts, and a consequence is that such locations will tend to have more variability in the age of housing. She therefore proposed using housing age variability as a proxy for these non-planned developments, and demonstrated in a study of Chicago neighborhoods that residents in such neighborhoods report higher levels of cohesion, social exchange, social control, and intergenerational closure. These measures are all typically proposed as mechanisms in neighborhoods that will result in less crime (Sampson and Groves 1989; Sampson, Raudenbush, and Earls 1997). We therefore propose testing here whether the variability in the age of housing is related to lower levels of crime.

Proper geographic scale of these theories?

A question is at what geographic scale we should expect the theories just discussed to operate. One perspective is that theories describing crime opportunities will operate at a micro-geographic scale. Thus, these opportunities would impact the level of crime in the immediate environment of the street segment. This would imply measuring the type of housing, the age of housing, or the mix of housing ages, in the focal segment to assess the impact on crime. However, if we consider the fact that offenders typically travel non-trivial distances to offending locations (Bernasco 2010; Bernasco, Ruiter, and Block 2016; Rossmo 2000), arguably a scale larger than the street segment is appropriate (Hipp and Boessen 2015). This would imply that there are spillover effects based on housing characteristics surrounding the segment. As a consequence, the ages and types of housing in surrounding segments may have an additional effect on the level of crime.

When assessing the appropriate scale of measuring housing age, and hence possible physical disorder, an important question is the spatial extent to which potential offenders perceive physical disorder as a cue to a potentially more desirable location for offending. The disorder on a single segment may be too small a scale, and it may be that physical disorder on several adjacent segments is needed for offenders to perceive an area as more vulnerable. St. Jean (2007) noted that offenders use physical disorder as cues about an area that is typically larger than a single street segment. We assess this possibility here.

Data and methods

Data

Housing type and crime

The study site is Los Angeles County. We combined data obtained from several police agencies in the county along with parcel-level data on housing characteristics obtained from the Los Angeles County Open Data Portal (https://data.lacounty.gov/). The units of analysis are all street segments in cities for which we have crime data.

Dependent variable

The crime data come from the Southern California Crime Study (SCCS), and were collected for three years (2009-11) and summed to minimize year-to-year fluctuations.[1] Crime events were geocoded for each city separately to latitude–longitude point locations using a geographic information system (ArcGIS 10.2) and placed to the nearest segment based on geographic proximity. Given that characteristics of crime incidents at intersections are not different from those on street segments, dropping them is not appropriate. For the small percentage of events at intersections we evenly assigned them to contiguous street segments (thus, a crime incident occurring on a typical intersection where two roads cross would assign to each of the four segments 0.25 of a crime). The geocoding match rate was 96.4%.

Independent variables

Our key independent variables account for the age and type of housing on a segment. We have information on each parcel in the county, which allows us to classify each housing structure and aggregate them to the segment. We used information on the age of each housing unit on a street to compute the *average housing age* and the *average housing age squared* (to account for nonlinear effects). To account for the possibility that the mix of housing ages may be important,

[1] We do not compute the average over the three year period given that this would yield non-integer values, which are not appropriate for Poisson models. By summing over the three years, our outcome variable is capturing the number of crime events over a three-year period. The coefficients can easily be scaled if one wishes to have a one-year interpretation.

we constructed a measure of the *standard deviation of housing age*; this captures the variability of housing ages.

We accounted for the type of housing by using information to categorize each parcel into one of six housing types and then to compute the proportion of units on each segment that are classified in each of these categories: 1) *detached single family units*; 2) *attached single family units*; 3) *duplexes*; 4) *small apartments (3-4 units)*; 5) *large apartments (more than 5 units)*; 6) *mobile homes*. The denominator for each of these is total number of residential housing parcels. In segments with no residential housing parcels, we set each of these 6 variables to zero.

To account for the composition of housing ages or housing types in the broader area around the segment, we also constructed the same measures aggregated to the ½ mile buffer surrounding the segment (with an inverse distance decay effect under the assumption that closer segments have a stronger impact on the segment). We measured this based on Euclidean distance from the centroid of each street segment. We tested shorter and longer distances (1/4 and ¾ mile) and the results were very similar.

For the housing age mixing variable, we measured the ½ mile buffer *without* a distance decay effect (an "egohood"), given the evidence of Hipp and Boessen (2013) that egohood measures better capture the relationship between heterogeneity measures and crime. An egohood takes a segment as the center point and then incorporates all other segments within a particular-sized buffer to be part of the same egohood. The presumption is that this is a unit of interest analogous to a neighborhood, but is presumed to approximately capture the activity patterns of residents. Therefore egohoods are overlapping "waves washing across the surface of cities" (Hipp and Boessen 2013: 287).

Control variables

Housing type and crime

To minimize the possibility of obtaining spurious results, we also included several other measures that prior literature has shown are important predictors of the level of crime in small geographic locations. These variables are all constructed at both the segment level and the broader ½ mile buffer surrounding the segment (with an inverse distance decay effect).

We constructed several socio-demographic variables based on the 2010 U.S. Census and the American Community Survey 5-year estimates for 2008-12. We account for the possibility that a larger local population impacts the level of crime by constructing measures of *population (logged)* and the squared version of this measure (to account for nonlinear effects). We measure *residential stability* by creating standardized versions of the percent home owners and the average length of residence (z-scores) and summing them. We capture *concentrated disadvantage* with a factor score of four variables: which combines the following measures in a factor analysis: 1) percent at or below 125% of the poverty level; 2) percent single parent households; 3) average household income; and 4) percent with at least a bachelor's degree. Whereas the measure of single parent households is available at the block level, the other three measures are only available at the block group level and therefore we used synthetic estimation for ecological inference (Cohen and Zhang 1988; Steinberg 1979) to assign these values to the blocks within the block group (Boessen and Hipp 2015).[2]

[2] Thus, the synthetic estimation for ecological inference approach estimates a model predicting the presence of a variable of interest at a larger geographic unit of analysis, and then uses the parameter estimates for the variables in this model and multiplies them by the values of these variables in a smaller unit of analysis to impute values of the missing variable in the smaller units. This approach assumes that the relationship between variables at one unit of analysis is similar at a different level, rather than assuming that there is no relationship at all, as is the assumption in the more typical strategy of uniform imputation. Boessen and Hipp assessed the properties of this approach with a small-scale simulation comparing to the more traditional approach of aggregation in an online appendix (https://onlinelibrary.wiley.com/action/downloadSupplement?doi=10.1111%2F1745-9125.12074&attachmentId=117311654). Their results show that this approach can yield estimates close to the true values, in contrast to the traditional approach. We estimated a model at the block group level predicting the variable of interest, and then used the parameter estimates from this model to impute values at the block level. The following variables were included in these imputation models: percent owners, racial composition, percent divorced

Housing type and crime

We constructed measures of the racial/ethnic composition as the *percent black*, *percent Latino*, and *percent Asian* (with percent white and other race as the reference category). We account for racial/ethnic mixing by measuring *racial/ethnic heterogeneity* based on the Herfindahl index (based on five categories of black, Latino, Asian, white and other race): this measure is computed as 1 minus a sum of squares of the proportion of each group. Larger values indicate more heterogeneous areas. We capture the opportunities provided by vacant units with the *percent vacant units* in the area. We include a measure of the *percent aged 16 to 29* to capture those in the prime offending ages. To then apportion the U.S. Census block data to street segments, we used the simple average approach described by Kim (2016). This approach uses information on the population of the two blocks that compose the segment to create a weighted mean of the variables of interest for the segment. Kim (2016) demonstrated the validity of this approach compared to more complicated strategies that account for the number of housing units on the side of a street in a street segment.

The presence of businesses and general land use can also impact the location of crime. We account for businesses with measures based on Reference USA (Infogroup 2015) data for 2010. This is address-level data that we directly aggregated to street segments. We capture the general presence of workers with the *number of total employees*. Given that retail and restaurants can attract customers to an area, we computed the *number of retail employees* and the *number of restaurant employees*. Although there are various "risky facilities" that might be associated with higher levels of crime, prior studies have most consistently shown that bars and liquor stores tend to operate as crime attractors (Groff and Lockwood 2014; Lipton and

---

households, percent households with children, percent vacant units, population density, and age structure (percent aged: 0-4, 5-14, 20-24, 25-29, 30-44, 45-64, 65 and up, with percent aged 15-19 as the reference category).

Gruenewald 2002; Murray and Roncek 2008; Ratcliffe 2012); we therefore constructed measures of the *number of bar employees* and the *number of liquor store employees*.[3] Finally, we account for the land use characteristics with parcel-level information obtained from the Southern California Association of Governments for 2008.[4] Prior studies have shown that industrial areas (Boessen and Hipp 2015; Stucky and Ottensmann 2009) and vacant land (Galster, Tatian, Santiago, Pettit, and Smith 2003; Raleigh and Galster 2014; Smith, Frazee, and Davison 2000; Stucky and Ottensmann 2009) operate to increase crime opportunities, and we therefore constructed measures of land use as the *percent industrial land use* and the *percent vacant land use*. The summary statistics for the variables used in the analyses are displayed in Table 1. Regarding the distribution of crime incidents, about 80% of segments have no aggravated assaults over three years, 17% have 1 to 3, and 3% have more than 3. The other two violent crimes are even rarer, as 90% and 99% have no robberies or homicides, respectively, whereas just 1% have more than 3. Property crimes are more frequent, as 67%, 75%, and 62% of segments have no burglaries, motor vehicle thefts, or larcenies, respectively, whereas 4%, 4%, and 7% have more than 3.

<<<Table 1 about here>>>

Methods

The outcome variables are crime counts in segments, and given their relative rarity we estimated the models as negative binomial regressions. This approach assumes a Poisson

[3] We tested ancillary models that calculated these variables as the number of firms, rather than employees. Our main results of interest were very similar. The model fit was slightly better for our models using the employee variables, so we present those results.

[4] Although some restaurants may serve alcohol, and therefore be similar to bars in their effect on crime, others may not. Given that we suspect they may have different relationships with crime, we included them as separate measures in the models. Although they had generally similar effects in the models, the size of the coefficients typically differed and therefore our model specification is improved by including them separately.

distribution to the crime count, but allows for overdispersion. The models included all of the control variables.

Results

We begin by focusing on the effects for our housing age measures, and in Table 2 we detect a relatively robust positive relationship between this measure and all six types of crime. Given the nonlinear effects detected for four of the crime types, we plot the relationships in Figure 1. Robbery and homicide both exhibit linear relationships with the age of housing in the segment: a ten year increase in the average housing age on a segment is associated with 5.5% more robberies and 16% more homicides (exp(.0054*10)=1.055 and exp(.0149*10)=1.161). The other four crime types exhibit slowing positive relationships as the age of housing increases, with two of them (aggravated assaults and motor vehicle thefts) actually showing a small reduction in crime rates in the oldest housing areas. Thus, we see that in the early years of housing the level of aggravated assault exhibits a very strong positive relationship with housing age: the rate of aggravated assaults is about 40% higher in a segment with an average age of 20 years compared to one with an average age of 10 years. Likewise, burglaries, motor vehicle thefts, and larcenies are 30%, 25%, and 18% higher in a segment with housing average aged 20 years compared to one average aged 10 years, even controlling for the other variables in the models. For segments with an average age of housing beyond 65 years, it appears that levels of aggravated assault and motor vehicle theft actually begin falling compared to segments with middle-aged housing.

<<<Table 2 about here>>>

<<<Figure 1 about here>>>

Whereas we find a robust positive relationship between the age of housing in the segment and the level of crime, the results are more mixed regarding the age of the housing in the area surrounding the segment. A one standard deviation increase in average housing age in the surrounding area is associated with 40% *fewer* aggravated assaults, but 11.5% *more* motor vehicle thefts. However, the coefficients are not statistically significant for the other crime types.

Turning to the measure of housing age mixing, segments with more housing age mixing have *higher* levels of all types of crime, controlling for these measures in the model. These segemnts have more violent crime, as a one standard deviation increase in housing age mixing is associated with 12%, 10%, and 33% more aggravated assaults, robberies, and homicides, respectively. There is also more property crime, as a one standard deviation increase in housing age mixing is associated with about 9-10% more of the three property crimes.

In contrast, we see that greater housing age mixing in the surrounding area is generally associated with lower crime rates. This is more in line with the findings of King (2013), as a one standard deviation increase in housing age mixing in the surrounding area is associated with 12%, 4% and 5% fewer aggravated assaults, motor vehicle thefts, and larcenies, respectively. There is no evidence of such spatial effects for the other three crime types (robberies, homicides, and burglaries).

Turning to the relationships between types of housing and crime rates, we detect very strong positive effects for nearly all crime types. All of these coefficients are compared to the reference category: detached single family units. To interpret the magnitude of these effects, in Figure 2 we present the odds ratios for change in crime when a segment is composed entirely of the measure of interest compared to one of all detached single family units. The most notable pattern from this figure is that nearly all of these other housing types are associated with higher levels of crime compared to detached single family units. The pattern is strongest for attached single family units and large apartment units (more than 5 units). A segment with all attached single family units will have 150% to 320% more violent crime and 140% to 290% more property crime than a segment with all detached single family units, controlling for the variables in this model. A segment with all large apartment buildings has about 280% more of the violent crimes of aggravated assault and homicide, about 200% more motor vehicle thefts and larcenies, and 70% and 130% more burglaries and robberies, respectively. Segments with all small apartments (3-4 units) have from 80% to 180% more crime than segments with detached single family units for all crime types except burglaries. A segment with all mobile homes has 210% more aggravate assaults, and 140% to 160% more motor vehicle thefts and larcenies than a segment with all detached single family units. Segments with all duplexes have 50-100% more aggravated assaults and robberies, and 40-70% more motor vehicle thefts and larcenies than one with all detached single family units.

<<<Figure 2>>>

Finally, we turn to the housing composition in the surrounding area, and the pattern of effects for these measures is more mixed. Figure 3 plots the partially standardized coefficients for the spatial buffer measures from the models, as they show the incident rate ratio change in crime for a one standard deviation change in the housing type in the surrounding area. The strongest positive effects are seen for segments surrounded by more duplexes. A segment surrounded by areas with one standard deviation more duplexes have 15.5% more aggravated assaults, 11% more robberies, and 6% more burglaries. There is some evidence that segments surrounded by one standard deviation more attached single family units have more larcenies (about 5% more), though they have about 14% fewer aggravated assaults compared to areas surround by detached single family units. But these effects are much smaller than those measured at the segment level. Furthermore, segments surrounded by more apartment units tend to have lower crime rates, especially if the surrounding area has large apartment units. Segments surrounded by smaller apartment units have about 10% fewer burglaries and motor vehicle thefts and 17% fewer robberies. Segments surrounded by larger apartment units have about 9% fewer burglaries and motor vehicle thefts and nearly 25% fewer violent crimes (aggravated assault and homicides). Finally, segments surrounded by more mobile homes have 5-8% fewer burglaries and larcenies.

<<<Figure 3 about here>>>

Sensitivity Analyses

Whereas filtering theory posits that housing units will experience dilapidation as they age, which we have suggested may lead to more disorder and hence more crime, it is also the case that older units can be renovated and improved (i.e., gentrification). Indeed, the nonlinear effects we detected for the relationship between housing age and four of the types of crime might capture this gentrification effect to some extent, as we saw that there is no evidence of a positive relationship in street segments with very old housing. Nonetheless, to more directly assess whether this impacts our results, we obtained building permit data for Los Angeles County and computed measures of the number of renovations done in the last 5 years (or last 10 years) on the segment (and also the total dollar amount of these renovations). When including these additional measures in the models, our main findings remained unchanged (and were slightly stronger in some instances). Thus, our results remained robust to these additional measures.

Conclusion

This study explored the relationship between the age or type of housing and the level of crime at micro locations. Based on theoretical insights from crime pattern theory, we took into account the type of housing, and based on the insights of filtering theory that we introduced here to the criminology field, we took into account the age of housing. And based on the theoretical insights of Jacobs we took into account the variance in the age of housing both on the segment and in the surrounding area. Our results showed strong relationships between the types of housing and the amount of crime on segments, suggesting that this is an important feature for police agencies to take into account when determining the likely location of crime incidents. And housing age—both the average and its variance—was a notable predictor of the location of crime. Ours is one of the first studies to empirically examine how housing types and housing age are both related to the spatial location of crime.

Our first key finding was that, consistent with filtering theory, segments with older aged housing tend to have higher levels of crime when controlling for the socio-demographic characteristics of the area. We proposed that older housing, ceteris paribus, will typically have more deterioration and hence more physical disorder. The implication is that such areas would then have more crime, and we found this was indeed the case for all six crime types. We emphasize that this theory implies a slow decline in housing quality, and therefore deterioration will only appear slowly if upkeep is not maintained. Furthermore, we emphasize that this deterioration is not irreversible: indeed, residents can repair their homes and engage in upkeep that maintains it at relatively high quality. Nonetheless, this deterioration is something that will be present for housing units that do not engage in upkeep, and therefore we have posited that, *on average*, older housing will have more physical disorder as a consequence. In some instances residents will engage in dramatic levels of work on housing units, and such instances will characterize neighborhoods undergoing gentrification. This may in part explain why we observed nonlinear effects for housing age and crime in which there was no evidence of a positive relationship for very old housing for four types of crime—in such instances it may be that the area has undergone gentrification (although our direct measure of housing unit improvement based on building permits in ancillary models did not capture this effect). This appeared to be a micro-spatial effect, as it was robustly present at the level of street segments, but not when measuring the broader area around the segment. Our findings highlight that scholars should take into account the age of housing when exploring the location of crime.

A second important finding is that whereas we hypothesized that the variance in housing age would be negatively related to levels of crime, this relationship was generally not found. Contrary to expectations, such segments actually had higher levels of all types of crime. Thus, although King (2013) used variance in housing age as a proxy for non-planned developments in the city of Chicago, and then found that such neighborhoods had higher levels of social interaction and cohesion, we did not find such an effect here for crime when measured at the micro-scale. One possible explanation is that in Southern California, as a prototypical Sunbelt community with sprawling development, this measure does not operate as a clean proxy for non-planned development compared to an older city such as Chicago. Another possibility is that we were measuring variance in housing age at too small a unit of analysis: King used larger neighborhoods, whereas we measured it at segments. Thus, we found that higher levels of housing age variance in the ½ mile egohood around a segment is associated with lower levels of aggravated assaults, motor vehicle thefts, and larcenies. The variance in housing age at this larger scale may capture a geographic unit more akin to a "neighborhoods", and therefore better capture the possible neighborhood cohesion that King referred to. Nonetheless, this effect was much weaker than the micro-effect we detected in street segments.

Housing type and crime

A third important finding was that the type of housing on a segment, and in the surrounding area, helped explain the location of crime. The effects were particularly strong, as crime is far less likely to occur on segments with detached single family units compared to other types of housing. Furthermore, there were distinctions in levels of crime between various types of multi-family units, as large apartment complexes and attached single family units typically experience more crime of all types compared to small apartment complexes (3-5 units). It may be that the anonymity associated with these larger complexes is more conducive to crime. This reinforces the importance of drilling down to more fine grained measures of housing units (Kinney et al. 2008), rather than just making a distinction between detached single family units and other types of housing . This suggests that a useful direction for future research is to account for more detailed characteristics of these apartment complexes to determine the mechanism(s) driving such effects.

A final important finding was that the housing age and housing types in the area *surrounding* the segment also were related to the location of crime. We measured the nearby area as a ½ mile buffer, and our results indicated that the types of housing in this area helped explain the number of crime events in the segment itself. Thus, there is not simply a micro-effect of housing type on crime at a specific location, but a more meso-level effect that typically has not been considered in prior work. For example, whereas street segments with large apartment complexes generally experience more crime, a greater presence of these large complexes in the surrounding area is associated with *lower* levels of crime. Why these different scale effects is present is not clear; one possibility is that whereas the micro effect captures crime opportunities at such locations, the meso effect captures the relative presence of offenders living at such locations (Hipp 2016). Keep in mind that this effect was detected even when accounting for the socio-demographic characteristics of the segment and the surrounding area, as well as measures of the business environment, suggesting that there is something additional that is being captured by these measures of housing types. Given that the Southern California region is largely defined by post-World War II housing developments that have a degree of uniformity, this may imply that the meso-level surrounding area – beyond the segment but shy of a mile – impact the level of crime on the segments throughout them. Such a possibility is under-theorized in the existing literature.

We acknowledge some limitations to this study. First, the broad categories of housing types that we used are a crude proxy for opportunities induced based on crime pattern theory. Nonetheless, the strong results demonstrate that these are useful measures. Second, whereas housing age is a direct measure of filtering theory and is meaningful for understanding the trajectory of a neighborhood, it is not in and of itself a measure of dilapidation and disorder. Third, our analyses were cross-sectional. This does not rule out the possibility of feedback effects in which the level of crime affects characteristics of the neighborhood. However, in our case, housing age is independent of the level of crime, and housing types that are present over time are unlikely to be impacted by crime. The main concern would be if certain types of housing are built in an area based on the level of crime. Given the slowness of change in the physical housing stock, we believe this likely has very little impact on our results. Fourth, there is always concern of under-reporting of crime when using official crime reports from police agencies. This would cause concern if there is systematic under-reporting based on the type or age of housing, but we are not aware of such systematic bias. The fact that one study found minimal evidence of systematic bias when reporting the serious types of crime studied here is encouraging, but the concern nonetheless remains (Baumer 2002).

Housing type and crime

In conclusion, this study has demonstrated that housing age and housing types are useful measures for criminologists to take into account when assessing the level of crime at micro locations. As predicted by filtering theory, older housing age was related to higher levels of crime. And consistent with crime pattern theory, segments with more detached single family housing units typically had lower levels of crime for all crime types. This is not simply a socio-economic effect, or a residential stability effect, as we controlled for these measures. Furthermore, our results demonstrated that these are not simply micro-geographic relationships, but that the age and type of housing in a ½ mile buffer surrounding a segment also impacted the level of crime in the segment. These results indicate that taking into account the physical features of the environment based on the housing stock is useful for understanding the location of crime.

References

Baer, William C. and Christopher B. Williamson. 1988. "The Filtering of Households and Housing Units." *Journal of Planning Literature* 3:127-152.

Barthe, Emmanuel P., Matthew C. Leone, and B. Grant Stitt. 2014. "Trailer Parks as Hotbeds of Crime: Fact or Fiction?" *Issues in Social Science* 2.

Barton, Michael S. 2016. "Gentrification and Violent Crime in New York City." *Crime & Delinquency* 62:1180-1202.

Baumer, Eric P. 2002. "Neighborhood Disadvantage and Police Notification by Victims of Violence." *Criminology* 40:579-616.

Bernasco, Wim. 2010. "A Sentimental Journey to Crime: Effects of Residential History on Crime Location Choice." *Criminology* 48:389-416.

Bernasco, Wim, Stijn Ruiter, and Richard Block. 2016. "Do Street Robbery Location Choices Vary Over Time of Day or Day of Week? A Test in Chicago." *Journal of Research in Crime and Delinquency* Forthcoming:1-33.

Boessen, Adam and John R. Hipp. 2015. "Close-ups and the scale of ecology: Land uses and the geography of social context and crime." *Criminology* 53:399-426.

Boggess, Lyndsay N. and John R. Hipp. 2016. "The Spatial Dimensions of Gentrification and the Consequences for Neighborhood Crime." *Justice Quarterly* 33:584-613.

Bowers, Kate. 2014. "Risky Facilities: Crime Radiators or Crime Absorbers? A Comparison of Internal and External Levels of Theft." *Journal of Quantitative Criminology* 30:389-414.

Brantingham, Patricia L. and Paul J. Brantingham. 1993. "Nodes, Paths and Edges: Considerations on the Complexity of Crime and the Physical Environment." *Journal of Environmental Psychology* 13:3-28.

—. 2008. "Crime Pattern Theory." Pp. 78-93 in *Environmental Criminology and Crime Analysis*, edited by R. Wortley and L. Mazerolle. Portland, OR: Willan Publishing.

Chang, Dongkuk. 2011. "Social Crime or Spatial Crime? Exploring the Effects of Social, Economical, and Spatial Factors on Burglary Rates." *Environment and Behavior* 43:26-52.

Cohen, Lawrence E. and Marcus Felson. 1979. "Social Change and Crime Rate Trends: A Routine Activity Approach." *American Sociological Review* 44:588-608.

Cohen, Michael Lee and Xiao Di Zhang. 1988. "The Difficulty of Improving Statistical Synthetic Estimation." Bureau of the Census, Washington, D.C.

Contreras, Christopher. 2016. "A Block-Level Analysis of Medical Marijuana Dispensaries and Crime in the City of Los Angeles." *Justice Quarterly* Forthcoming.

Coulson, N. Edward and Eric W. Bond. 1990. "A Hedonic Approach to Residential Succession." *The Review of Economics and Statistics* 72:433-444.

Cui, Lin and Randall Walsh. 2015. "Foreclosure, vacancy and crime." *Journal of Urban Economics* 87:72-84.

Delmelle, Elizabeth C. 2015. "Five Decades of Neighborhood Classifications and their Transitions: A Comparison of Four US Cities, 1970-2010." *Applied Geography* 57:1-11.

Deryol, Rustu, Pamela Wilcox, Matthew Logan, and John Wooldredge. 2016. "Crime Places in Context: An Illustration of the Multilevel Nature of Hot Spot Development." *Journal of Quantitative Criminology* 32:305-325.

Ellen, Ingrid Gould and Katherine M. O'Regan. 2011. "How low income neighborhoods change: Entry, exit, and enhancement." *Regional Science and Urban Economics* 41:89-97.

Felson, Marcus. 2002. *Crime and Everyday Life*. Thousand Oaks, CA: Sage.

Housing type and crime

Freeman, Lance and Tiancheng Cai. 2015. "White Entry into Black Neighborhoods: Advent of a New Era?" *The ANNALS of the American Academy of Political and Social Science* 660:302-318.

Galster, George C., Peter A. Tatian, Anna M. Santiago, Kathryn L.S. Pettit, and Robin E. Smith. 2003. *Why Not in My Backyard? Neighborhood Impacts of Deconcentrating Assisted Housing*. New Brunswick, NJ: Rutgers.

Gault, Martha and Eric Silver. 2008. "Spuriousness or mediation? Broken windows according to Sampson and Raudenbush (1999)." *Journal of Criminal Justice* 36:240-243.

Groff, Elizabeth R. and Brian Lockwood. 2014. "Criminogenic Facilities and Crime across Street Segments in Philadelphia: Uncovering Evidence about the Spatial Extent of Facility Influence." *Journal of Research in Crime and Delinquency* 51:277-314.

Hipp, John R. 2016. "General theory of spatial crime patterns." *Criminology* 54:653-679.

Hipp, John R. and Adam Boessen. 2013. "Egohoods as waves washing across the city: A new measure of “neighborhoods”." *Criminology* 51:287-327.

—. 2015. "Neighborhoods, Networks, and Crime." in *Challenging Criminological Theory: The Legacy of Ruth Kornhauser*, edited by F. T. Cullen, P. Wilcox, R. J. Sampson, and B. Dooley: Transaction.

Hoyt, Homer. 1933. *One Hundred Years of Land Values in Chicago*. Chicago: Dissertation.

Hwang, Jackelyn and Robert J. Sampson. 2014. "Divergent Pathways of Gentrification: Racial Inequality and the Social Order of Renewal in Chicago Neighborhoods." *American Sociological Review* 79:726-751.

Infogroup. 2015. "Reference USA Historical Business Data." edited by Infogroup. Papillion, NE: Reference USA.

Jacobs, Jane. 1961. *The Death and Life of Great American Cities*. New York: Random House.

Kim, Young-an. 2016. "Examining the Relationship Between the Structural Characteristics of Place and Crime by Imputing Census Block Data in Street Segments: Is the Pain Worth the Gain?" *Journal of Quantitative Criminology* Forthcoming.

King, Katherine. 2013. "Jane Jacobs and 'The Need for Aged Buildings': Neighborhood Historical Development Pace and Community Social Relations." *Urban Studies* 50:2407–2424.

Kinney, J. Bryan, Patricia L. Brantingham, Kathryn Wuschke, Michael G. Kirk, and Paul J. Brantingham. 2008. "Crime Attractors, Generators and Detractors: Land Use and Urban Crime Opportunities." *Built Environment* 34:62-74.

Kreager, Derek, Christopher J. Lyons, and Zachary R. Hays. 2011. "Urban Revitalization and Seattle Crime, 1982−2000." *Social Problems* 58:615-639.

Kubrin, Charis E. and John R. Hipp. 2016. "Do Fringe Banks Create Fringe Neighborhoods? Examining the Spatial Relationship between Fringe Banking and Neighborhood Crime Rates." *Justice Quarterly* 33:755-784.

Lipton, Robert and Paul Gruenewald. 2002. "The Spatial Dynamics of Violence and Alcohol Outlets." *Journal of Studies on Alcohol* 63:187-195.

Lowry, Ira S. 1960. "Filtering and housing standards: A conceptual analysis." *Land Economics* 36:362-370.

McCarty, William P. and Daniel P. Hepworth. 2013. "Mobile home parks and crime: Does proximity matter?" *Journal of Crime and Justice* 36:319-333.

Murray, Rebecca K. and Dennis W. Roncek. 2008. "Measuring Diffusion of Assaults Around Bars Through Radius and Adjacency Techniques." *Criminal Justice Review* 33:199-220.

Housing type and crime
Newman, Oscar. 1972. *Defensible Space: People and Design in the Violent City*. London: Architectural Press.
O'Brien, Daniel Tumminelli and Robert J. Sampson. 2015. "Public and Private Spheres of Neighborhood Disorder: Assessing Pathways to Violence Using Large-scale Digital Records." *Journal of Research in Crime and Delinquency* 52:486-510.
Owens, Ann. 2012. "Neighborhoods on the Rise: A Typology of Neighborhoods Experiencing Socioeconomic Ascent." *City & Community* 11:345-369.
Papachristos, Andrew V., Chris M. Smith, Mary L. Scherer, and Melissa A. Fugiero. 2011. "More Coffee, Less Crime? The Relationship between Gentrification and Neighborhood Crime Rates in Chicago, 1991 to 2005." *City & Community* 10:215-240.
Patino, Jorge E., Juan C. Duque, Josep E. Pardo-Pascual, and Luis A. Ruiz. 2014. "Using Remote Sensing to Assess the Relationship Between Crime and the Urban Layout." *Applied Geography* 55:48-60.
Raleigh, Erica and George Galster. 2014. "Neighborhood Disinvestment, Abandonment, and Crime Dynamics." *Journal of Urban Affairs*:online.
Ratcliffe, Jerry H. 2012. "The Spatial Extent of Criminogenic Places: A Changepoint Regression of Violence Around Bars." *Geographical Analysis* 44:302-320.
Roncek, Dennis W. and Pamela A. Maier. 1991. "Bars, Blocks, and Crimes Revisited: Linking the Theory of Routine Activities to the Empiricism of 'Hot Spots'." *Criminology* 29:725-753.
Rosenthal, Stuart S. 2014. "Are Private Markets and Filtering a Viable Source of Low-Income Housing? Estimates from a “Repeat Income” Model†." *American Economic Review* 104:687-706.
Ross, Catherine E., John Mirowsky, and Shana Pribesh. 2002. "Disadvantage, Disorder, and Urban Mistrust." *City and Community* 1:59-82.
Rossmo, D. Kim. 2000. *Geographic Profiling*. Boca Raton: CRC Press.
Sampson, Robert J. and W. Byron Groves. 1989. "Community Structure and Crime: Testing Social-Disorganization Theory." *American Journal of Sociology* 94:774-802.
Sampson, Robert J., Stephen W. Raudenbush, and Felton Earls. 1997. "Neighborhoods and Violent Crime: A Multilevel Study of Collective Efficacy." *Science* 277:918-924.
Skogan, Wesley G. 1986. "Fear of Crime and Neighborhood Change." Pp. 203-229 in *Communities and Crime*, vol. 8, edited by A. J. Reiss and M. Tonry. Chicago: University of Chicago Press.
—. 1990. *Disorder and Decline: Crime and the Spiral of Decay in American Neighborhoods*. New York: Free Press.
Smith, Lawrence B., Kenneth T. Rosen, and George Fallis. 1988. "Recent Developments in Economic Models of Housing Markets." *Journal of Economic Literature* 26:29-64.
Smith, William R., Sharon Glave Frazee, and Elizabeth L. Davison. 2000. "Furthering the Integration of Routine Activity and Social Disorganization Theories: Small Units of Analysis and the Study of Street Robbery as a Diffusion Process." *Criminology* 38:489-523.
St. Jean, Peter K.B. 2007. *Pockets of Crime: Broken Windows, Collective Efficacy, and the Criminal Point of View*. Chicago: University of Chicago.
Steenbeek, Wouter, Beate Völker, Henk Flap, and Frank van Oort. 2012. "Local Businesses as Attractors or Preventers of Neighborhood Disorder." *Journal of Research in Crime and Delinquency* 49:213-248.

Steinberg, Joseph. 1979. "Synthetic Estimates for Small Areas: Statistical Workshop Papers and Discussion." Pp. 282 in *National Institute on Drug Abuse Research Monograph Series*, vol. 24. Washington, D.C.: National Institute on Drug Abuse.

Stucky, Thomas D. and John R. Ottensmann. 2009. "Land Use and Violent Crime." *Criminology* 47:1223-1264.

Taylor, Ralph B. 1996. "Neighborhood Responses to Disorder and Local Attachments: The Systemic Model of Attachment, Social Disorganization, and Neighborhood Use Value." *Sociological Forum* 11:41-74.

—. 1997. "Social Order and Disorder of Street Blocks and Neighborhoods: Ecology, Microecology, and the Systemic Model of Social Disorganization." *Journal of Research in Crime and Delinquency* 34:113-155.

Taylor, Ralph B. and Jeanette Covington. 1988. "Neighborhood Changes in Ecology and Violence." *Criminology* 26:553-589.

Theodos, Brett, Claudia J. Coulton, and Rob Pitingolo. 2015. "Housing Unit Turnover and the Socioeconomic Mix of Low-Income Neighborhoods." *The ANNALS of the American Academy of Political and Social Science* 660:117-135.

Weisburd, David, Elizabeth Groff, and Sue-Ming Yang. 2012. *The Criminology of Place*. New York: Oxford.

Wilson, James Q. and George Kelling. 1982. "Broken Windows: The Police and Neighborhood Safety." *Atlantic Monthly*:10.

Tables and Figures

Table 1. Summary statistics for variables used in analyses

	Focal segment					Surrounding buffer			
	Mean	Std Dev	Min	Max		Mean	Std Dev	Min	Max
Average age of housing (/100)	52.7	21.0	0.7	109.0		51.6	17.0	2.0	96.0
Standard deviation of housing age	7.6	9.3	0.0	69.3		1539.9	675.1	0.0	4525.5
Proportion attached single family units	0.021	0.122	0.0	1.0		0.087	0.143	0.000	0.991
Proportion duplexes	0.066	0.173	0.0	1.0		0.054	0.079	0.000	0.600
Proportion small apartments (3-4 units)	0.053	0.160	0.0	1.0		0.034	0.051	0.000	1.000
Proportion large apartments (5+ units)	0.092	0.250	0.0	1.0		0.033	0.058	0.000	0.961
Proportion mobile homes	0.005	0.061	0.0	1.0		0.002	0.018	0.000	1.000
Proportion industrial land use	0.018	0.116	0.0	1.0		0.043	0.077	0.000	0.792
Proportion vacant lots	0.044	0.186	0.0	1.0		0.082	0.163	0.000	1.000
Concentrated disadvantage	-1.20	9.18	-28.42	31.40		-0.15	8.03	-18.91	27.50
Residential stability	0.09	0.74	-4.06	2.52		0.15	0.71	-4.56	2.24
Racial/ethnic heterogeneity	0.437	0.177	0.000	0.775		0.483	0.163	0.000	0.926
Percent black	8.5	15.8	0.0	100.0		8.5	13.8	0.0	100.0
Percent Latino	38.4	29.6	0.0	100.0		40.1	27.8	0.0	100.0
Percent Asian	11.3	14.4	0.0	100.0		11.4	12.8	0.0	100.0
Percent occupied units	94.8	5.7	0.0	100.0		94.4	3.8	0.0	100.0
Percent aged 16 to 29	20.1	7.1	0.0	100.0		21.1	5.6	0.0	100.0
Population	4.96	0.94	0.00	8.05		0.26	0.18	0.00	1.73
Total employees (logged)	0.63	1.17	0.00	9.91		6.72	1.60	0.00	11.67
Retail employees (logged)	0.13	0.53	0.00	7.78		4.43	1.85	0.00	10.02
Bar employees (logged)	0.00	0.08	0.00	4.39		0.00	0.00	0.00	0.00
Liquor store employees (logged)	0.01	0.09	0.00	3.93		0.00	0.00	0.00	0.00
Restaurant employees (logged)	0.07	0.43	0.00	6.15		0.00	0.00	0.00	0.00

Note: N= 109,216 segments. Population in segment is logged; population in surrounding buffer is per 1000

Table 2. Negative binomial regression models for segments in Los Angeles County cities in 2010

	Aggravated assault	Robbery	Homicide	Burglary	Motor vehicle theft	Larceny
Housing type						
Percent attached single family units	1.3369 **	0.9199 **	1.4288 †	0.8667 **	1.3596 **	1.1343 **
	(12.58)	(5.96)	(1.91)	(11.86)	(15.79)	(20.08)
Percent duplexes	0.7055 **	0.3974 **	0.6035	0.0957 †	0.5488 **	0.362 **
	(11.04)	(4.35)	(1.48)	(1.73)	(9.34)	(7.16)
Percent with 3-4 units	0.9249 **	0.6479 **	1.0393 **	0.1553 **	0.609 **	0.578 **
	(15.32)	(7.62)	(2.79)	(2.82)	(10.79)	(12.12)
Percent with 5 or more units	1.3386 **	0.8487 **	1.3539 **	0.5227 **	1.1196 **	1.0969 **
	(28.61)	(12.61)	(4.32)	(13.02)	(26.62)	(33.59)
Percent mobile homes	1.1333 **	0.3959	1.2621	0.3145	0.8521 **	0.9566 **
	(6.88)	(1.01)	(0.97)	(1.61)	(4.37)	(6.77)
Average lot size (single family units)	-0.0079	0.0201	0.0224	-0.0381 †	-0.0083	-0.0388 *
	-(0.30)	(0.40)	(0.11)	-(1.81)	-(0.28)	-(2.17)
Housing age						
Average age of housing	0.0404 **	0.0054 **	0.0149 *	0.0299 **	0.0262 **	0.0183 **
	(15.98)	(4.05)	(2.41)	(14.71)	(10.48)	(10.57)
Average age of housing squared	-0.0003 **			-0.0002 **	-0.0002 **	-0.0001 **
	-(12.39)			-(12.11)	-(8.35)	-(8.33)
Standard deviation of housing age	0.0122 **	0.0096 **	0.0301 **	0.0095 **	0.0104 **	0.0088 **
	(9.50)	(5.48)	(3.94)	(9.42)	(9.04)	(9.82)
Housing type in surrounding area						
Percent attached single family units	-1.0475 **	-0.3635 †	-0.8003	-0.1463 †	-0.1307	0.3303 **
	-(8.33)	-(1.93)	-(0.89)	-(1.71)	-(1.19)	(4.71)
Percent duplexes	1.8248 **	1.3106 **	-0.6874	0.7819 **	0.0276	0.1773
	(8.68)	(4.31)	-(0.47)	(4.10)	(0.14)	(1.05)
Percent with 3-4 units	-0.2651	-3.7735 **	-1.593	-2.3321 **	-2.3579 **	-0.9489 **
	-(0.80)	-(8.43)	-(0.78)	-(7.97)	-(7.88)	-(3.81)
Percent with 5 or more units	-4.6848 **	-0.6846 †	-4.5502 *	-1.5677 **	-1.4858 **	-0.2699
	-(14.21)	-(1.87)	-(2.25)	-(6.48)	-(5.87)	-(1.41)
Percent mobile homes	-1.2165	-6.9523	2.1532	-3.1376 *	0.9445	-4.5764 **
	-(0.79)	-(1.11)	(0.24)	-(2.08)	(0.46)	-(3.19)
Average lot size (single family units)	0.0210	0.1546 †	0.1905	0.1052 **	-0.0054	0.0425
	(0.46)	(1.75)	(0.54)	(3.20)	-(0.10)	(1.48)
Housing age in surrounding area						
Average age of housing	-0.0303 **	0.0029	-0.0167 †	-0.0003	0.0064 **	0.001
	-(21.65)	(1.31)	-(1.72)	-(0.25)	(4.78)	(1.04)
Standard deviation of housing age (X 100)	-0.0195 **	0.0045	0.0060	-0.0013	-0.0065 **	-0.0082 **
	-(8.88)	(1.37)	(0.42)	-(0.74)	-(3.16)	-(5.34)
R-square	0.224	0.177	0.000	0.091	0.200	0.122

*Note: ** p < .01; * p < .05; † p < .10. T-values in parentheses. N= 109,216 segments. Negative binomial regression models. All models include the following control variables at the segment and spatial lag level: logged population and squared, percent industrial land use, percent vacant land use, concentrated disadantage, residential stability, racial/ethnic heterogeneity, percent Black, percent Latino, percent Asian, percent occupied units, percent aged 16 to 29, total employees, retail employees, bar employees, liquor store employees, restaurant employees.*

Housing type and crime

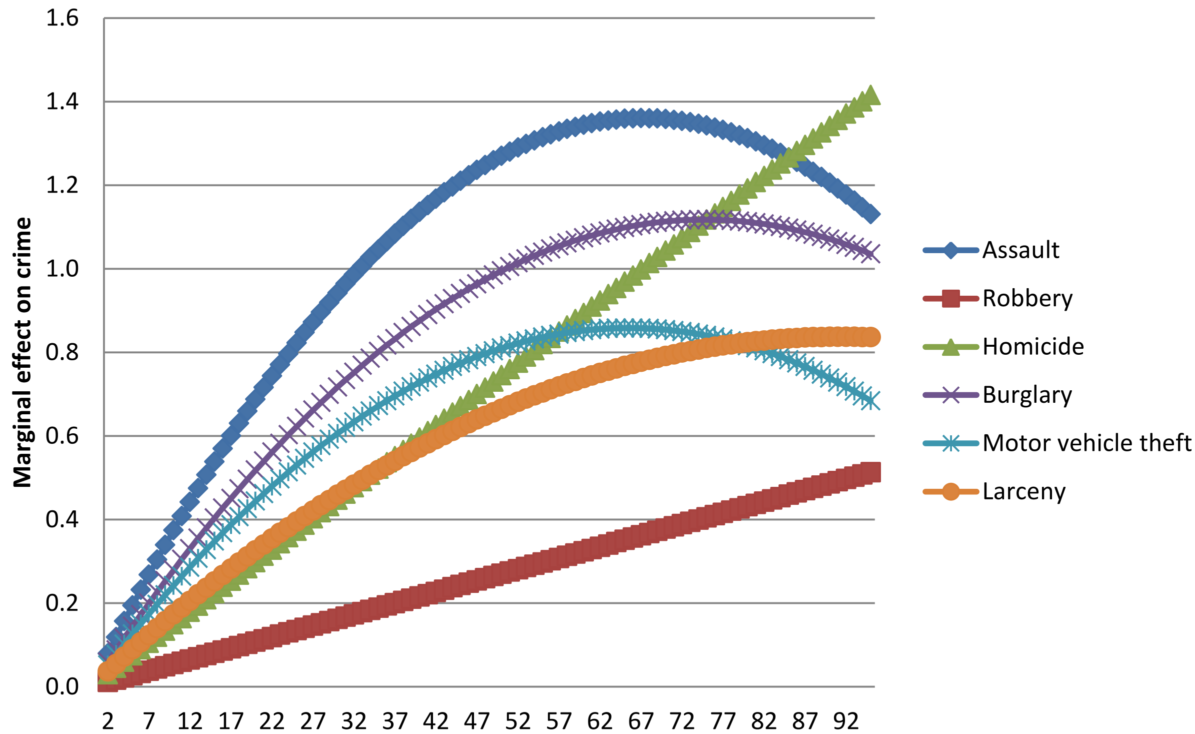

Figure 1. Relationship between segment average housing age and crime

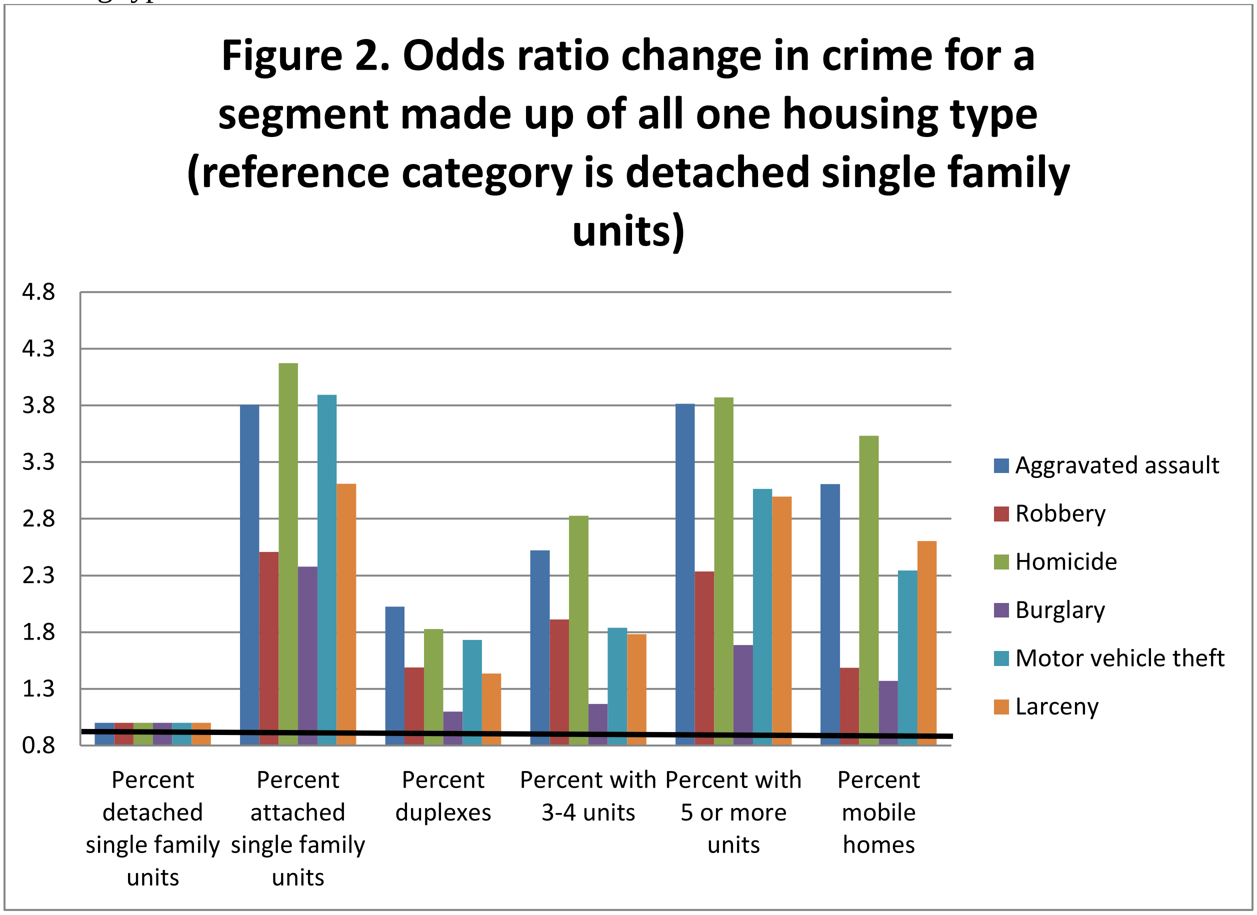
Figure 2. Odds ratio change in crime for a segment made up of all one housing type (reference category is detached single family units)
4.8
4.3
3.8
3.3
2.8
2.3
1.8
1.3
0.8
Percent detached single family units
Percent attached single family units
Percent duplexes
Percent with 3-4 units
Percent with 5 or more units
Percent mobile homes
Aggravated assault
Robbery
Homicide
Burglary
Motor vehicle theft
Larceny

Housing type and crime