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Drive-bys and Trade-ups:

Examining the Directionality of the Crime and Residential Instability Relationship

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Drive-bys and Trade-ups:

Examining the Directionality of the Crime and Residential Instability Relationship

Abstract

Most prior research testing the hypothesis of the social disorganization theory that residential instability increases crime has used cross-sectional data. Using a unique dataset linking home sales geocoded to census tracts with crime data in Los Angeles, we test the direction of this relationship using a six-year panel data design. We also test whether crime acts as a generator of transition and decline in neighborhoods by testing its effect on property values the following year. Our findings suggest little evidence that home sales volatility in one year leads to more property or violent crime the following year. Instead, higher levels of tract property and violent crime in one year lead to more home sales the following year. This effect of high crime rates is exacerbated in tracts with high levels of racial/ethnic heterogeneity, suggesting that such tracts may engender a distinct combination of fear and uncertainty in their residents, leading to more turnover. We also find that tracts with more violent crime one year have lower property values the following year, suggesting a general process of decline.

Keywords: social disorganization, neighborhoods, crime, residential instability, racial/ethnic heterogeneity, dynamic, longitudinal, cross-lagged, spatial effects

Drive-bys and Trade-ups:

Examining the Directionality of the Crime and Residential Instability Relationship

Given the numerous studies demonstrating that neighborhood characteristics influence a variety of behaviors and outcomes at the individual level (for a review, see Sampson et al. 2002), social scientists have expended considerable effort in trying to understand the social processes responsible for these relationships. Though the majority of ecological research has focused on the impact of concentrated disadvantage as the primary structural dimension that affects outcomes, the roles of residential stability and home ownership, along with ethnic heterogeneity, have also garnered significant attention. Each of these is explicitly linked to mobility, as the flow of people into and out of neighborhoods transforms neighborhoods. With respect to local levels of disadvantage/affluence, scholars have therefore studied the characteristics of the populations that leave, stay, or enter anew into a neighborhood to explain why some neighborhoods experience an economic downward spiral (Wilson 1987) while others gentrify (Beauregard 1990, Galster et al. 2003). Residential change also helps to explain why some neighborhoods undergo racial/ethnic transformation (Massey & Denton 1993, Massey & Mullan 1984), and why some neighborhoods plunge into a state of disorder as rates of residential instability increase (Skogan 1990).

Recent work has suggested that the level of crime in neighborhoods may play an integral role in shaping neighborhood mobility patterns. Crime will drive neighborhood transformation if residents respond to crime through increased mobility, as this will increase residential instability (Cullen & Levitt 1999, Dugan 1999, Liska & Bellair 1995, Liska et al. 1998, Marshall 1979, Morenoff & Sampson 1997, Skogan 1990). Disadvantage may become more concentrated if

crime makes a neighborhood less desirable and reduces home values (Schwartz et al. 2003, Tita et al. 2006). Furthermore, if the characteristics of residents moving into such neighborhoods differ systematically based on race/ethnicity as a result of increased rates of crime, one possible result is increased racial/ethnic heterogeneity (Bursik 1986, South & Crowder 1997b). Indeed, scholars have argued that high crime areas can get caught in self-perpetuating crime cycles (Felson 2002, Miethe & Meier 1994, Skogan 1990). This suggests a need for a theoretical model that takes these mobility decisions into account, and is consistent with a recent call to theoretically integrate the interrelationship between crime and residential mobility (Liska & Bellair 1995: 604, South & Messner 2000).

Although the social disorganization model posits that three key structural characteristics—poverty, ethnic heterogeneity, and residential instability—increase crime by affecting the patterns of social interaction among residents in a neighborhood, which then affects the willingness to engage in various guardianship activities that might reduce the rate of neighborhood crime (Park & Burgess 1921, Sampson & Groves 1989, Shaw & McKay 1942), the challenge is teasing out the interdependencies between these structural characteristics and crime rates. While a body of research has focused on specifying and testing the posited mechanisms for these structural characteristics, this literature has almost exclusively employed cross-sectional data, obviating the ability to consider the possible effect of crime on these structural characteristics (Bellair 1997, 2000, Hirschfield & Bowers 1997, Sampson & Groves 1989, Sampson & Raudenbush 1999, Smith et al. 2000, Veysey & Messner 1999, Warner 2003, Warner & Pierce 1993). These studies frequently simply assume a unidirectional causal relationship from instability to crime. However, while the instability caused by "trade ups" is likely to increase crime when those with the necessary resources are able to transition out of less

desirable into more desirable neighborhoods, crime, such as "drive by" shootings, is also likely an important generator of neighborhood transition.

Despite the role crime likely plays in triggering neighborhood transformation, empirical investigation is limited. The few studies that have tested for a reciprocal relationship between crime rates and residential mobility flows utilized large cities and metropolitan areas as the units of analysis (Liska & Bellair 1995, Liska et al. 1998, Marshall 1979). Nonetheless, using large cities as the unit of analysis is arguably too large to capture the more *meso* level of neighborhoods hypothesized by the social disorganization theory (Hipp 2007a). Such studies are also unable to discern whether the residents of the neighborhoods with the highest levels of crime are those most likely to move, but they instead must simply infer this from these highly aggregated units (running the risk of the ecological fallacy). Indeed, we are aware of no studies that have tested for a possible reciprocal relationship between crime and residential instability at the neighborhood level.

To address these questions, we employ longitudinal data from the city of Los Angeles between 1992 and 1997 to examine the directionality of the relationship between crime and one form of residential instability—home sales volatility—at the census tract level. We suggest that understanding the dual relationship between residential instability of owners and crime is a useful first step in addressing this question. We use simultaneous equation panel data models to examine both whether residential instability leads to increased crime in future years and/or whether higher levels of crime lead to housing turnover in subsequent years. Our models account for possible spatial effects with time-lagged spatial lags of the outcome measures. We further examine whether this crime also leads to decreasing property values in such neighborhoods, signifying a general process of decline. Finally, we link this question to the

racial transformation literature and ask whether crime exacerbates the instability of

neighborhoods experiencing racial/ethnic mixing.

The paper proceeds as follows: We first outline social disorganization theory and then

develop a model of residential mobility, highlighting the importance of neighborhood crime in

shaping mobility decisions. We consider theoretically whether this crime sparks a general

decline in such neighborhoods through falling property values. Next, we describe the data and

methodology and present the results of cross-lagged models that simultaneously test the

relationship between crime in one year and residential instability the following year and the

reverse relationship. Relying upon our empirical findings, we conclude with a call for social

disorganization models to more fully explore possible reciprocal relationships between crime and

neighborhood instability.

Theoretical Underpinnings

Social disorganization theory: Residential instability causing crime

The social disorganization model posits that structural conditions of neighborhoods—the

level of poverty, residential instability, and racial/ethnic heterogeneity—will affect the social

interactions of residents, which then impact the ability of residents to act collectively in response

to neighborhood crime and disorder (Park & Burgess 1921, Sampson & Groves 1989, Shaw &

McKay 1942). In this perspective, the banding together of residents in a neighborhood through

informal networks or through voluntary organizations allows them to respond to problems as

they arise and results in such neighborhoods having lower levels of crime (Crenshaw & St. John

1989, Friedman 1998, Guest & Oropesa 1984, Taub et al. 1984). This allows a neighborhood "to

realize the common values of its residents and maintain effective social controls" (Sampson &

Groves 1989: 777). Thus, neighborhoods with more residential instability, poverty, or

racial/ethnic heterogeneity will have less social organization and hence more crime (Bellair

1997, Hipp 2007b, Roncek & Maier 1991, Rountree & Warner 1999, Sampson & Groves 1989,

Smith et al. 2000, Warner & Pierce 1993, Warner & Rountree 1997). Reduced ties among

residents is posited to diminish the willingness of residents to intervene—either informally by

confronting potential problems directly, or formally by joining organizations that are oriented

towards addressing the root causes of crime in neighborhoods–to address problems when they

arise in the neighborhood.

Although there is a voluminous literature purporting to test these hypotheses of the social

disorganization theory, it is important to emphasize that these tests are almost exclusively

conducted with cross-sectional data. For instance, several studies have detected a positive

association between neighborhood instability and crime rates (Bellair 1997, 2000, Heitgerd &

Robert J. Bursik 1987, McNulty & Holloway 2000, Warner & Pierce 1993, Warner & Rountree

1997). Despite the robustness of these findings, a commonality is their failure to consider the

plausible hypothesis that higher rates of crime give rise to more residential mobility. That is, an

appropriate test is not whether there is an association between residential instability and crime at

a point in time but rather whether residential instability in one year causes more crime at some

point *in the future*.

We test this possible dual relationship by using longitudinal data on one form of

residential instability—that of homeowners. Given that owners on average exhibit considerably

more residential stability than do renters and that owners know more neighbors (Austin & Baba

1990, Hunter 1975, Logan & Spitze 1994) and are more likely to be involved in the sort of

neighborhood associations that the social disorganization model posits reduce crime (Oliver

1984, Taub et al. 1977), we suggest that residential stability among owners may be particularly important for understanding local levels of crime. This implies the following hypothesis:

Hypothesis 1: Neighborhoods with a higher level of home sales volatility in one year will have higher rates of crime the following year

Crime causing residential mobility

Much of the work in the social disorganization literature assumes that households are constrained to particular neighborhoods and that household responses to neighborhood problems are constrained to joining neighborhood associations, participating in activities designed to combat crime, or simply shrinking from social life (Gerson et al. 1977, Perkins et al. 1990, Skogan 1989, Taylor 1996). The collective efficacy literature follows in this tradition and focuses on the possibility that residents can proactively affect crime and disorder in the neighborhood through various actions. These models rarely explicitly consider the possibility that residents may choose to respond to neighborhood problems by moving out of the neighborhood.

There is a certain irony in the observation that recent work in the social disorganization field almost completely disregards the possibility of mobility decisions in response to crime, as the initial formulation of the social disorganization model explicitly discussed mobility decisions (Park & Burgess 1921, Shaw & McKay 1942). That is, the initial formulation of social disorganization posited that neighborhoods evolved over time as ecologies and that particular levels of crime and disorder characterized particular neighborhoods. In this implicit economic choice model, households choose to move to the most desirable neighborhoods—those with the least amount of crime and disorder—based on their level of economic resources. Thus, the

model captured mobility of residents *to* neighborhoods based on the level of crime in the neighborhood but did not explicitly incorporate into the theoretical model the possibility that residents would move *from* neighborhoods based on the level of crime. As a result of this key distinction, a recent wave of research testing the mechanisms of social disorganization has effectively ignored the possibility that residents may choose to leave neighborhoods with high rates of crime. Indeed, one study in this vein suggested that households may choose to leave a community in trouble, yet nonetheless tested the effect of residential instability on community cohesion using cross-sectional data (Kasarda & Janowitz 1974). We suggest that it is not enough to simply casually note the possibility that residents may leave a neighborhood in response to the level of crime, but we assert that such decisions have important implications for cross-sectional tests of the social disorganization theory.

Although Shaw and McKay did not explicitly consider whether higher rates of crime could induce greater residential mobility out of a neighborhood, we suggest that households indeed desire neighborhoods with less crime. As a consequence, higher rates of crime will lead to more mobility. For instance, Skogan (1990) found that crime rates cause dissatisfaction and a desire to move in a study of 40 neighborhoods. Although South and Deane (1993) found no effect of *perceived* crime for mobility decisions, a study found significant effects for *actual* crime events experienced (Dugan 1999). Studies have also tested this possible relationship using aggregated units of analysis. For instance, Morenoff and Sampson (1997) found that census tracts in Chicago with high numbers of homicides led to general population losses, and Cullen and Levitt (1999) found a similar effect using cities as the unit of analysis.

However, while it is clear why residents would prefer to flee a neighborhood with increasing levels of crime, it is less obvious why other residents would be willing to move *into*

such neighborhoods. We suggest two possible explanations. First, there is likely an asymmetry of information. That is, the residents leaving a neighborhood are more intimately aware of the actual level of crime and disorder—which is not always apparent to someone viewing a neighborhood for the first time—and therefore may be more averse to the neighborhood. The prospective new household may be less aware of such problems: Indeed, there is evidence that households who have lived longer in the neighborhood perceive more crime (Sampson et al. 1997) and more risk of crime (Taylor et al. 1984). Another study found that residents who lived longer in the neighborhood expressed more fear of walking in their local block at night and more fear of walking in the broader neighborhood both during the day *and* night (Taylor 2001).

Second, to the extent that potential new residents are in fact aware of increasing problems in a neighborhood, there should be downward pressure on home values. Indeed, studies have shown that neighborhoods with higher rates of crime have lower home values (e.g., Buck & Hakim 1989, Schwartz et al. 2003, Thaler 1978), and that neighborhoods experiencing increasing levels of crime will undergo falling relative home values (Tita et al. 2006). There is therefore suggestive evidence that crime can be a catalyst for a downward trajectory in a neighborhood through increasing out-mobility and falling home values. Thus, lower housing prices will attract residents who otherwise would not be able to afford to buy a home in the neighborhood.

In summary, asymmetric flows of information between potential sellers and buyers should result in crime raising home sales while an increased awareness of crime on the buyers' part will suppress housing prices. More formally, this is stated in the following two hypotheses:

Hypothesis 2: Neighborhoods with higher levels of crime in one year will have higher rates of home sales the following year

Hypothesis 3: Neighborhoods with higher levels of crime in one year will have lower property values the following year

Beyond its effect on residential turnover and a downward economic trajectory, crime induced mobility may also be intertwined with the process of racial/ethnic transformation. The residential segregation literature has long noted the clustering of racial/ethnic groups in the neighborhoods of metropolitan areas in the U.S. (Massey & Denton 1987, 1993). Given this clustering and the implied preference for a neighborhood with relative homogeneity along race/ethnicity—at least among white residents (Clark 1991, 1992, Emerson et al. 2001, Farley et al. 1997, Krysan 2002a, b)—this suggests that neighborhoods with more mixing of racial/ethnic groups may be particularly at risk for a downward spiral. For one thing, given that racial/ethnic mixing is often an unstable equilibrium (Schelling 1978, Thompson 2000), neighborhoods with more racial/ethnic mixing are likely undergoing racial/ethnic transformation that leads to higher levels of residential mobility as a consequence. Furthermore, this racial/ethnic heterogeneity likely reduces the number of neighbor ties (Connerly & Marans 1985, Sampson 1991), which can affect neighborhood satisfaction (Connerly & Marans 1985, Sampson 1991), which then affects residential mobility (Speare 1974). Although the connection between racial/ethnic heterogeneity and residential mobility appears straightforward, very few tests of this hypothesis exist. We test this here.

Hypothesis 4*:* Neighborhoods with higher levels of racial/ethnic heterogeneity will have higher rates of home sales in following years

While racial/ethnic heterogeneity likely increases residential mobility, building on the insights of the social disorganization literature there are numerous reasons to suspect that neighborhood racial/ethnic heterogeneity and neighborhood crime work in tandem to increase

residential mobility. First, there is evidence that racial/ethnic difference fosters uncertainty and

mistrust by reducing the social interaction between residents (Connerly & Marans 1985,

Sampson 1991). Second, studies have shown that racial/ethnic heterogeneity increases the

perception of crime and disorder in the neighborhood on the part of residents (Hipp 2007a,

Sampson & Raudenbush 2004). Third, studies have shown that crime fosters fear and

uncertainty about the environment (Rountree & Land 1996a, b). Given these overlapping

processes, it is likely that neighborhoods experiencing both crime and racial/ethnic transition are

acutely undesirable settings in which to reside. That is, residents may perceive crime events as

particularly unsettling when they occur in an environment lacking a network structure that allows

residents to form more comforting symbolic structures with fellow residents about the

neighborhood's relative safety. These considerations suggest the following hypothesis, of which

we are aware of no tests.

Hypothesis 5: In neighborhoods with higher levels of crime, the effect of racial/ethnic

heterogeneity on rates of home sales the next year will be heightened

Summary

        We have suggested that crime might act as a catalyst for neighborhood change along

various dimensions. Based on our review above, at least two possibilities are equally plausible:

Neighborhood-level residential mobility may cause more crime, as suggested by the social

disorganization model, or crime may cause more residential instability, as implied by our review

of the literature. We therefore employ a cross lagged model on six-year panel data of tracts in

the city of Los Angeles (1992-97), which allows us to 1) test whether residential instability

among property owners in one year affects the level of crime in the next year; 2) simultaneously

test whether the level of crime in one year affects the rate of home sales the following year; 3)

test whether crime also reduces the neighborhood's property values the following year; and 4)

test whether crime exacerbates the effect of racial/ethnic heterogeneity on home sales volatility.

Data and Methodology

Outcome measures

Our key outcome measures are the amount of crime in the tract and the volatility of home

sales (residential instability). We measure crime using data obtained directly from the Los

Angeles Police Department on the number of violent crimes per 100,000 population and the

number of property crimes per 100,000 population.[1] These data were provided for police

reporting districts, which are generally nearly coterminous with census tracts. We placed these

crime data into census tracts and log transformed the measures to obtain a better approximation

of a normal distribution.[2] We obtained home sales data from Dataquick, Inc. and geocoded all

home sales into the appropriate census tract.[3] We calculated home sales volatility as the number

of home sales transactions divided by the total number of owner occupied units in the tract.

Thus, we are effectively measuring the proportion of owned homes that were sold during the

year. We constructed these measures for each of our study years from 1992 to 1997. While

there are 713 tracts in Los Angeles during this time period, we excluded from the analysis tracts

with populations of fewer than 900 persons or fewer than 200 owner occupied units, leaving us

with a final sample of 600 tracts. These excluded tracts are not of interest given their potential

high variability on one of our key measures—home sales volatility—due to the small

denominator of owner occupied units. Nonetheless, we assessed the robustness of these cutoff

values by estimating ancillary models with alternative cutoff values of 1) 100 owner occupied

units and 500 persons, and 2) 300 owner occupied units and 1,500 persons. Our main substantive results were unchanged in these ancillary models (results available upon request).

In additional models we included as an outcome a measure of housing values based on the sales prices of houses that sold in a census tract during a given year. Simply using the median tract sales price would be misleading. For instance, if in one year most of the home sales in a neighborhood involved only smaller houses and the following year most of the sales involved larger houses, a naïve approach using the median home value would mistakenly conclude that values in the neighborhood have increased, when in fact only a change in the composition of homes sold has occurred. Instead, we use a hedonic approach that takes into account the characteristics of the specific homes sold in order to provide a more appropriate comparison over time. To do this, we regressed the logged value of the house on key characteristics of the housing unit and accounted for the neighborhood by including indicator variables for all 600 tracts minus one (the reference tract).[4] The estimated coefficients for these tract indicator variables give us an unbiased estimate of the property value in each of the tracts, relative to the reference tract.[5] We then included these estimated relative tract property values as the outcome in our dynamic models of neighborhood change.

Crime outcome model

In the equation predicting violent or property crime, we took into account several measures from the 1990 U.S. Census that are likely important predictors of crime. While we would ideally have information for these measures in each year of the analysis, there is little year-to-year change in several of these measures, such as racial/ethnic composition (Ellen, (2000: 145). To take into account the racial/ethnic composition of the tract, we included measures of the proportion Asian, African-American, Latino, and other race (with proportion

white as the reference category). Social disorganization theory suggests that social interaction

will be reduced when individuals differ based on race/ethnicity, thus we created a measure of

racial/ethnic heterogeneity as a Herfindahl index (Gibbs & Martin 1962) of the same five

racial/ethnic groups described above, which takes the following form:

$$(1) \qquad H = 1 - \sum_{j=1}^{J} G_j^2$$

where G represents the proportion of the population of ethnic group *j* out of *J* ethnic groups.[6]

Subtracting from 1 makes this a measure of heterogeneity. *H* Ranges from 0, completely

homogeneous to 0.8, completely heterogeneous.[7]

To account for neighborhood economic resources that the social disorganization theory

posits are helpful in obtaining resources from the larger community for addressing neighborhood

crime, we included the tract median home value and the proportion of the population at or below

125% of the poverty rate. To capture the effect of broken families that might reduce oversight

capability, we included the proportion divorced in the tract. We measured general residential

stability as the average length of residence of households in the tract in 1990. Thus, we are

controlling for the long-run relationship between residential instability and crime when

estimating the short-term relationship between crime and home sales volatility. We account for

the effect of neighborhood abandonment by including the proportion of occupied units in the

tract. We account for the greater investment of owners by including the proportion of tract

households who own their residence. Population density is included to account for the negative

impact of anonymity on informal control often observed in densely populated neighborhoods.

Residential mobility outcome

In the equation predicting home sales volatility, we included a number of aggregated

measures that past studies have shown are important at the household level for mobility

decisions. These variables capture three key perspectives in predicting mobility decisions. First is the notion that life course dictates decisions to move (McAuley & Nutty 1982, Rossi 1955). We accounted for this by including the measure of the proportion divorced. Second is the notion that sunk costs in a housing unit will affect decisions to move (Rossi 1955). We accounted for this by including the measures of residential stability and the proportion of households who own their home. Third, scholars argue that households require the resources to act upon desires to leave the neighborhood (Landale & Guest 1985). To measure the existence of economic opportunities, we included measures of the median home value and the proportion of households at or below 125% of the poverty level. To the extent that mobility options are more limited for minority groups, we took into account the racial/ethnic composition of the tract (white, African-American, Latino, Asian, and other).

We also included several measures to capture neighborhood desirability. Because the presence of nearby vacant units may reduce desirability and thus increase mobility, we included the proportion of occupied units. To account for over-crowding, which may also reduce desirability, we included population density. Graduation rates of the local schools are used as a proxy for the quality of education. This measure is taken from the Local Education Agency (School District) Universe Survey Longitudinal Data File: 1986-1997 (U.S. Department of Education 2001).[8] Finally, to test the hypothesis that racial/ethnic heterogeneity affects mobility decisions, we included this construct as defined above. We list the summary statistics of the variables used in the analyses in Table 1. The outcome measures of home sales volatility and logged crime rates all exhibit relative normality (low kurtosis values, and skewness absolute values all less than one).

<<<Table 1 about here>>>

Methodology

We focus on estimating the dual relationship between the crime rate and home sales volatility. Given that the relationship between changing crime rates and mobility decisions is not instantaneous, a lag model is appropriate. We model one-year lags given that homeowners responding to crime likely require a year to sell their houses and move. Lags are also appropriate given that instability arguably slowly breaks down social ties and leads to more crime in the future rather than in a more instantaneous fashion.[9] Thus, our model specifies that the crime rate in one year causes greater home sales volatility the next year, while home sales volatility in one year affects the crime rate the next year. The theoretical model we test is depicted in Figure 1.

<<<Figure 1 about here>>>

This implies a model with two equations:

(2) $$sales_{(t)} = \rho_{1(t)}\, sales_{(t-1)} + \beta_{1(t)}\, crime_{(t-1)} + \varepsilon_{1(t)}$$

(3) $$crime_{(t)} = \rho_{2(t)}\, crime_{(t-1)} + \beta_{2(t)}\, sales_{(t-1)} + \varepsilon_{2(t)}$$

where $sales_{(t)}$ is the proportion of homes sold during year t, $sales_{(t-1)}$ is the proportion of homes sold during year $t-1$ (the previous year), $crime_{(t)}$ is the natural logged crime rate during year t, $crime_{(t-1)}$ is the crime rate during year $t-1$ (the previous year), the coefficient $\rho_{1(t)}$ captures the effect of the proportion of property sales in the previous year on the proportion of property sales in the current year, $\rho_{2(t)}$ captures the effect of the crime rate in the previous year on the crime rate in the current year, the coefficient $\beta_{1(t)}$ captures the effect of the crime rate in the previous year on the proportion of property sales in the current year, $\beta_{2(t)}$ captures the effect of the proportion of property sales in the previous year on the crime rate in the current year, and $\varepsilon_{1(t)}$ and $\varepsilon_{2(t)}$ are disturbance terms at each time point t. We model additional possible autocorrelation not accounted for in this model by allowing the disturbances for a particular outcome to correlate

over time in adjacent years (that is, we allowed $\varepsilon_{1(t)}$ to covary with $\varepsilon_{1(t-1)}$ and we allowed $\varepsilon_{2(t)}$ to

covary with $\varepsilon_{2(t-1)}$).[10] We also allowed the disturbances between the two constructs to covary

within time points in case omitted variables from each of these equations induce such a

correlation (that is, we allowed $\varepsilon_{1(t)}$ to covary with $\varepsilon_{2(t)}$).[11] To take into account possible

heteroskedasticity in these error terms over time, we estimated a separate value for each

disturbance at each time point. Note that because we are specifying a one-year lag effect of our

predictors (and not simultaneous effects), this is a recursive model and thus does not pose any

particular identification difficulties (for a complete discussion of identification issues in such

models, see Bollen 1989).

This model is extended by taking into account the socio-demographic characteristics of

the census tract. Because we only have information from the decennial census rather than from

each time point, these additional variables enter the model as time-invariant predictors,

modifying equations 2 and 3 thusly:

(4) $$sales_{(t)} = \rho_{1(t)}\, sales_{(t-1)} + \beta_{1(t)}\, crime_{(t-1)} + \Gamma_1 X + \varepsilon_{1(t)}$$

(5) $$crime_{(t)} = \rho_{2(t)}\, crime_{(t-1)} + \beta_{2(t)}\, sales_{(t-1)} + \Gamma_2 X + \varepsilon_{2(t)}$$

where X is a matrix of variables from the 1990 census, the vector Γ_1 shows the effect of these

variables on the proportion of property sales at time t, and the vector Γ_2 shows the effect of these

variables on the crime rate at time t. Note that our model is taking into account time fixed effects

because it is estimating each time-point equation separately.

In the most unconstrained model, we can estimate separate values for Γ_1, Γ_2, β_1, β_2, ρ_1,

and ρ_2 at each time point. We can also estimate a second model that constrains these values to

be equal over time points and determine the decrement in fit by imposing these constraints.

Doing so showed that constraining the effect of these variables to be equal over time provides

more gain in parsimony than it does in decrement of fit as judged by the Bayesian Information Criterion (BIC), which decreases from 4222.712 to 4002.956 when constraining these parameters equal over time (smaller values indicate better fit). Therefore, we present the models constraining these coefficients to be equal over waves. This model is also theoretically justified because there is little reason to expect the *effects* of these measures to vary from one year to the next.

Testing for spatial effects

Because our data come from census tracts that are located in physical space, we needed to account for possible spatial effects of adjacent neighborhoods. To determine what constitutes "close" neighborhoods, we adopted a distance decay function with a cutoff at two miles (beyond which the neighborhoods have a value of zero in the weighting matrix, *W*) to measure the distance of surrounding neighborhoods from the focal neighborhood (based on the tract centroids). Given that past studies have suggested a distance decay function for offenders (Rengert et al. 1999) with an average distance traveled between 1 to 2.5 miles (Pyle 1974) and that the median census tract in 1990 was about 1.4 miles across (2 square miles), we suggest this is a reasonable choice for a weight matrix. This resulting *W* was then row-standardized (that is, the inverse distances of the nearby neighborhoods from the focal neighborhood sum to one) to constrain each neighbor to impact the focal tract proportionately.

Whereas most spatial tests are constructed for cross-sectional relationships, our cross-lagged longitudinal model requires special consideration. There are two possible forms of spatial effects: a spatial autocorrelation (or, error) effect, or a spatial lag effect. In the spatial autocorrelation model, there is an additional relationship among the *residuals* of neighboring tracts. This is generally considered the less serious form of spatial effect, as it primarily affects

the standard errors, typically inflating them and thus decreasing the ability to detect effects

(Anselin 2002). In the spatial lag model, the outcome measure in the neighboring tract causally

affects the level of the outcome in the tract of interest. Failure to correct for the spatial lag, if it

belongs in the model, equates to omitted variable bias and leads to incorrect estimates of the

regression coefficients when the goal of the estimation is to discover the direct effects of the

measures on the outcome.

Because we are using a lagged model in which the measures causally affect outcomes one

year later, it is appropriate in such a model to take into account spatial lag effects by, for

instance, including the time-lagged spatially-lagged values of the proportion of home sales in the

surrounding tracts from the previous time point in the equation predicting the proportion of sales

at the current time point. That is, equations 4 and 5 are now modified such that

(6) $\qquad sales_{(t)} = \rho_3(W)sales_{(t-1)} + \rho_{1(t)}\,sales_{(t-1)} + \beta_{1(t)}\,crime_{(t-1)} + T_1X + \varepsilon_{1(t)}$

(7) $\qquad crime_{(t)} = \rho_4(W)crime_{(t-1)} + \rho_{2(t)}\,crime_{(t-1)} + \beta_{2(t)}\,sales_{(t-1)} + \Gamma_2X + \varepsilon_{2(t)}$

where ρ_3 represents the spatial autoregressive parameter that measures the impact of the rate of

transactions in neighboring tracts in the previous year on the rate of transactions in a tract in the

current year, W is the chosen spatial weighting matrix, $(W)sales$ represents the spatially lagged

dependent variable in the sales equation, ρ_4 represents the spatial autoregressive parameter that

measures the impact of the crime rate in neighboring tracts in the previous year on the crime rate

in a tract in the current year, $(W)crime$ represents the spatially lagged dependent variable in the

crime equation, and the remaining terms are defined as before. That is, we are testing whether

the home sales of neighboring tracts *in the previous year* affect home sales in the tract in the

current year, controlling for the other measures in the equation (such as the home sales in the

tract of interest in the previous year, and the crime rate in the tract of interest in the previous

year). The interpretation of the crime equation is analogous. Again, because these spatial effects

are specified as time-lagged, there are no specific identification difficulties with this model.

Further, we estimated an equation with the property values in the neighborhood (from our

fixed effects hedonic model described above) as the outcome. This equation is

(8) $$value_{(t)} = \rho_{5(t)}\, value_{(t-1)} + \beta_{3(t)}\, crime_{(t-1)} + \beta_{4(t)}(W)crime_{(t-1)} + \Gamma_2 X + \varepsilon_{3(t)}$$

where all values are defined as before, and value is the estimated average property value in the

tract after taking into account the characteristics of the homes in our fixed effects regression

model described above and ρ_5 is the effect of last year's property values on this year's values.

We treat the disturbances in these equations similarly to those in the other equations described

above.

Finally, we tested whether racial/ethnic heterogeneity moderated the effect of crime on

home sales volatility. Because we expect that the effect of racial/ethnic heterogeneity will

exacerbate the effect of high rates of crime on home sales volatility—but should not have an

effect at low rates of crime—we estimated a spline interaction. That is, we created two measures

of violent crime: 1) low crime (equal to the value of crime in the tract if it is less than the

citywide mean in 1992, otherwise it equals the mean 1992 value); 2) high crime (equal to the

value of crime, minus the citywide mean in 1992 if greater than that mean, otherwise it is equal

to zero). The spline approach is well-known (Greene 2000: 322-324) and is analogous to

piecewise linear trajectory models estimated with longitudinal data (Bollen & Curran 2006: 103-

105). We then created interactions of racial/ethnic heterogeneity with each of these measures.[12]

We tested and found no evidence of collinearity problems in our models given that all VIF

statistics were below 10 and that ancillary models showed robust effects with no evidence of

unstable estimates.[13] All models were estimated using a maximum likelihood estimator in Mplus 3.

Results

Violent crime and home sales volatility

We begin by focusing on the results of our cross-lagged models of violent crime and home sales volatility. The results of simultaneously estimating equations 6 and 7 are shown in columns 1 and 2 (model 1) of Table 2. First, we note that the expected autoregressive effects appear in both of these equations: A high rate of crime in a tract in the previous year increases the rate of crime in the current year ($\hat{\rho}_2 = 0.920$), and a high rate of home sales volatility in a tract in the previous year ($\hat{\rho}_1 = 0.975$) increases the rate of home sales in the current year, as seen in Table 2. This is a strong stasis effect, consistent with our model specification.[14] We also see significant time-lagged spatial lag effects as high rates of instability in neighboring tracts in the previous year ($\hat{\rho}_3 = 0.064$) increase the sales volatility in the current year, and high rates of crime in neighboring tracts in the previous year ($\hat{\rho}_4 = 0.028$) increase the crime rate in the tract of interest in the current year. Note as well that these models explain a considerable amount of the variance in these outcome measures: We are explaining, on average, 66% of the variance in the home sales volatility equations and 88% of the variance in the violent crime equations.[15]

<<<Table 2 about here>>>

We next turn to our key parameters of interest: the cross-lagged effects of violent crime on the rate of home sales the following year, and home sales volatility on violent crime the following year. First, we emphasize that there is no evidence that percent home sales in one year

results in higher rates of violent crime the following year (column 1). This finding directly

contradicts the social disorganization hypothesis that instability should foster increased crime.

On the other hand, we see direct evidence that higher crime rates in one year lead to higher home

sales volatility the following year ($\hat{\beta}_1 = 0.140$). This is consistent with the hypothesis that crime

is undesirable and residents desire to flee neighborhoods with higher rates of crime: For a tract

at the mean level of home sales, a one unit increase in violent crime increases the home sales

volatility rate 3 percent.[16] These twin results are particularly troubling for prior studies in the

social disorganization literature finding a cross-sectional relationship between instability and

crime and entirely attributing the causal relationship to the effect of residential instability on

crime. This model employing longitudinal data and one type of instability—home sales

volatility—shows no such effect.

Effects of control variables

We briefly note the effects of the control variables in this model. Turning first to the

equation predicting neighborhood violent crime rates, we see that tracts with higher levels of

racial/ethnic heterogeneity have higher levels of violent crime and that tracts with more owners,

higher home values, and more population density have lower rates of violent crime throughout

this time period. Note, however, that the measure of overall residential instability shows no

effect on the changing rate of violent crime over these years of the study.[17]

Turning to the model predicting home sales volatility, we see that tracts with higher

poverty, population density, owners, residential instability, and home values in 1990 have higher

home sales volatility throughout this time period. However, the main story here is the strong

racial/ethnic heterogeneity effects. To get an idea of the magnitude of these effects, we plotted

the marginal effect on home sales volatility for different racial/ethnic combinations in tracts. In

this exercise, we simulated the marginal effect on home sales volatility for seven hypothetical racial/ethnic compositions in neighborhoods: 1) 100% white, 2) 100% Latino, 3) 100% African-American, 4) half white and half Latino, 5) half white and half African-American, 6) half Latino and half African-American, 7) a high heterogeneity tract matching the proportions of one of the empirically most heterogeneous tracts in the sample. All other variables are held to their mean values. These effects are shown graphically in Figure 2 and make clear that the racial/ethnic mixing in the tract leads to more home sales volatility. There is also evidence that all-white tracts have high levels of instability. In contrast, all-Latino and all-black tracts—as well as mixed black-Latino tracts—experience the lowest levels of home sales volatility. These latter findings are consistent with the residential segregation literature suggesting that these two racial/ethnic groups are particularly constrained when it comes to neighborhood choice (Cutler et al. 1999, Flippen 2004, Kain & Quigley 1975, Rosenbaum 1994, South & Crowder 1997a, South & Deane 1993).

<<<Figure 2 about here>>>

Property crime and residential mobility

While we have seen robust effects for violent crime at one point increasing the rate of home sales the following year, we next tested whether the same relationship holds for property crime. As can be seen in columns 3 and 4 (model 2) of Table 2, which re-estimate equations 6 and 7 for property crime, the pattern of results is similar for property crime as it was for violent crime. There is no evidence that higher levels of home sales volatility increase the property crime rate the following year. Instead, higher property crime rates one year lead to increasing home sales volatility the following year.

We also estimated ancillary models in which we specified types of crime rather than the aggregated violent or property crime measures. The results were generally similar, as home sales volatility increased the following year 0.16 units for a one unit increase in aggravated assaults, 0.09 units for a one unit increase in robberies, 0.09 units for a one unit increase in murders, 0.13 units for a one unit increase in burglaries, and 0.11 units for a one unit increase in motor vehicle thefts (results not shown). In none of these models was there evidence that higher rates of home sales volatility in one year led to increases in any of these types of crime the following year.

Crime and property values

We next augmented our model by testing the effect of crime on property values the following year. As hypothesized, we see evidence of a downward spiral in neighborhoods with higher levels of violent crime, as they not only have more home sales volatility but they also experience decreasing property values. A one unit increase in violent crime results in a 1.6 percent drop in the estimated property values in the neighborhood the following year. On the other hand, the effect for property crime was about half the size (0.7 percent) and not statistically significant.

Testing for moderating effects of tract racial/ethnic heterogeneity

We next tested whether the racial/ethnic heterogeneity of the tract moderated the cross-lagged effect of crime on home sales volatility. As hypothesized, we found that the racial/ethnic heterogeneity of the tract significantly moderated the relationship between crime in one year and home sales volatility the following year, as shown in Table 3. We illustrate these effects graphically by plotting them in Figure 3, which shows that it is the combination of high racial/ethnic heterogeneity and high violent crime that leads to more home sales volatility. Our spline model illustrates that for tracts with low levels of crime, the amount of racial/ethnic

heterogeneity has little effect on home sales volatility (the left hand side of the graph). However, for tracts with high levels of crime, high levels of racial/ethnic heterogeneity have a particularly strong positive effect on home sales volatility. This suggests that these twin measures of uncertainty may foster a particularly high level of mistrust that increases the likelihood of abandoning the neighborhood. This moderating effect behaved similarly when replacing the violent crime measure with the measure of property crime, as shown in Figure 4.[18]

<<<Table 3 about here>>>

<<<Figure 3 about here>>>

<<<Figure 4 about here>>>

Finally, we estimated additional models testing whether the effect of homeowner residential mobility on neighborhood crime occurs as a conditional effect. That is, although we found no evidence of a main effect of residential mobility in the previous year increasing crime in the current year, we tested whether residential mobility affects crime only in certain circumstances: in economically deprived (as measured by median home values, or percent in poverty), racial/ethnic minority (percent African-American), or racially/ethnically heterogeneous tracts (racial/ethnic heterogeneity). We were thus testing whether these structural characteristics work multiplicatively with homeowner mobility. We found no evidence in these ancillary models that these measures interact with residential instability to increase the level of crime (results not shown). There is simply little evidence that annual homeowner residential mobility leads to more crime.

Conclusion

While much recent work in the social disorganization literature has tested the relationship between tract structural characteristics—or the posited mechanisms of the social disorganization model—and crime, these tests have almost exclusively utilized cross-sectional data. An important implication is that such research frequently does not theoretically take into account the possibility that households may respond to crime through residential mobility decisions. We have pointed out here that whereas studies occasionally acknowledge this possibility, they generally fail to consider the implications of such household decisions for testing the social disorganization model using cross-sectional data. We have highlighted that one clear implication is that researchers should explicitly model possible reciprocal relationships between crime and residential mobility. Furthermore, we have tested these effects with tract-level data, avoiding the limitation of testing such effects with data aggregated to the level of the city—arguably a level of aggregation too great to capture such dynamic neighborhood effects.

We have exploited a unique sample in which we linked information on crime rates in census tracts in Los Angeles with home sales information aggregated to the same census tracts. An advantage of this sample is that it allowed us to model the effects of residential instability and crime with one-year lags. Whereas studies using census data are constrained to ten-year lags to model these possible relationships (e.g., Liska & Bellair 1995, Morenoff & Sampson 1997)—which may well be too long to capture how residents respond to crime—our one-year lags comport with theoretical expectations of how residents may respond to crime. Thus, to our knowledge, ours is the first longitudinal test of tracts of the possible dual relations between these two constructs. And the fact that we were able to test these effects on a large sample of 600 census tracts over a six-year period only lends confidence to the findings reported here.

Our findings were clear: Whereas there was virtually no evidence that higher levels of residential instability by homeowners leads to greater levels of violent or property crime the following year, we saw evidence that higher levels of property or violent crime indeed led to greater rates of home sales the following year. These twin findings raise considerable uncertainty about the body of evidence purporting to test this relationship using cross-sectional data and assuming that the causal relationship runs unilaterally from residential instability to crime.

A second key finding was that neighborhoods with more violent crime not only experienced more home sales volatility, but they also experienced relative decreases in property values. This is consistent with the notion of a downward spiral experienced by such neighborhoods (Felson 2002, Miethe & Meier 1994, Skogan 1990). Thus, whereas we suggested that at least part of the reason that households may be "willing" to move into neighborhoods with increasing crime has to do with information asymmetry—that is, residents leaving the neighborhood may well be more aware of recent increases in crime than would prospective new residents—another part of the reason appears to simply be an economic one in which home values fall in response to this increase in crime. These findings are consistent with other studies finding an inverse relationship between changes in crime rates and housing values (Schwartz et al. 2003, Tita et al. 2006) and suggests a possible downward spiral for such neighborhoods in response to increasing crime rates. An important implication of this finding is the clear need for policies that help neighborhoods address rising crime rather than allowing such problems to evolve into a general decline in which residents abandon the neighborhood.

A third key finding of this study was the particularly strong effect of racial/ethnic heterogeneity on residential instability. That is, tracts with a higher level of racial/ethnic

heterogeneity in 1990 had higher levels of residential instability over the six years of data in our sample. This is consistent with the hypothesis we put forward that racial/ethnic heterogeneity is an unstable equilibrium (Schelling 1978, Thompson 2000) and will lead to greater residential mobility. This hypothesis was built upon the insights of previous work noting that racial/ethnic heterogeneity reduces the number of contacts between residents in neighborhoods, reduces neighborhood satisfaction, and reduces neighborhood cohesion and collective efficacy (Connerly & Marans 1985, Sampson 1991, Warner & Rountree 1997). The notion that racial/ethnic heterogeneity is undesirable for some residents and likely induces residential mobility ties in with the residential preference literature: Studies have consistently shown that whites have a much lower willingness to live in integrated neighborhoods than do other racial/ethnic groups (Bobo & Zubrinsky 1996, Emerson et al. 2001, Harris 2001, Krysan 2002a).

Our fourth key finding was the reinforcing effect in which violent and property crime rates along with racial/ethnic heterogeneity worked in concert to increase home sales volatility. Although higher rates of crime in racially/ethnically *homogeneous* tracts do not lead to higher rates of home sales the following year, high rates of violent crime in racially/ethnically *heterogeneous* tracts have a particularly strong effect on residential instability the following year. This is consistent with the hypothesis that the uncertainty fostered by a neighborhood with a mixed racial/ethnic composition, when combined with the frightening quality of crime, has a particularly strong effect on owners' desire to abandon the neighborhood. This finding raises important theoretical questions that future studies will need to address. Foremost among these is the question whether this combination of crime and racial/ethnic heterogeneity affects other decisions of households in such neighborhoods. For instance, if households are more likely to simply abandon a neighborhood that is experiencing a high level of violent crime in combination

with high racial/ethnic heterogeneity, might such neighborhoods also reduce the willingness of residents to engage in activities to improve the neighborhood? This might imply that residents in such neighborhoods would experience lowered perceived collective efficacy. Such a hypothesis would require a reorientation from the current preoccupation of studies employing collective efficacy as a construct that only affects—but is not affected by—crime and disorder. For instance, although Sampson and Raudenbush (1999) found a significant effect of crime on collective efficacy using simultaneous equations, few other studies have followed up on this insight.

While this study's unique sample design allowed us to test a key hypothesis of the social disorganization theory in a longitudinal framework, some limitations of our study should be acknowledged. We note that we were not able to measure overall residential instability in the tract, but rather we measured the instability fostered by home sales. How important is this distinction? We highlight that the social disorganization model makes no distinction between residential instability induced by renters moving out of the neighborhood and that induced by owners moving out. Should these two measures of instability have differential effects? No studies to date have posited, nor tested, such differences. This fact in itself, of course, does not discount the possibility that the instability of renters may be particularly important for fostering crime. However, we know of no plausible reason to expect renter instability to have a particularly important effect on crime rates, nor do we know of any studies that have disaggregated the effect of owners' and renters' residential stability on crime rates. Whereas the instability of renters on average is certainly higher than that of owners, this does not speak to the relationship between this mobility and crime rates. Indeed, one might argue that given renters' more mobile tendencies, the owners in a neighborhood are particularly important for fostering

residential stability. If this is the case, this suggests that our measure may be a reasonable approximation of overall residential stability.

In conclusion, we highlight the key insights our study provides for the social disorganization theory and call into question a key hypothesis of the theory. Prior studies limited to testing the relationship between residential instability and crime rates employing cross-sectional data are challenged by the findings in this study. Using longitudinal data, we showed that, if anything, there is stronger evidence that violent and property crime leads to more residential instability, rather than the reverse. We also found that violent crime led to lower property values the following year, suggestive of a general process of transition and decline in such neighborhoods. While we did find evidence in support of the social disorganization theory that racial/ethnic heterogeneity has important effects on violent crime, we did not find evidence to support the hypothesis that residential instability leads to increased crime. This suggests a need for future empirical tests of the social disorganization model to more explicitly consider the possibility that crime may induce residential mobility.

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Notes

[1] Violent crimes include robberies, aggravated assaults, and murders. Property crimes include burglaries, motor vehicle thefts, and larcenies.

[2] Although it is advisable to estimate negative binomial regression models when the count outcomes are relatively rare, our aggregated measures of violent and property crime have relatively large means such that the distribution approximates a normal distribution. Therefore, little would be gained by estimating a model treating the outcome with a Poisson distribution rather than the normal distribution.

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[4] The outcome measure was the logged sales price of the unit. We included the following housing unit measures in the model: logged square footage of the unit; logged square footage of the lot; the logged number of bedrooms; the logged number of bathrooms; an indicator for the presence of a swimming pool; an indicator of whether the unit has a garage; the age of the unit; squared age of the unit (to capture nonlinear effects); and indicators of the season of the sale. The logged form of specific measures was used given that it resulted in a better prediction of the logged sale price.

[5] An alternative approach to estimating these neighborhood property values would utilize a multilevel estimation strategy and obtain the empirical Bayes estimates for each micro-neighborhood. While a reasonable approach, this requires the additional assumptions that this random intercept is normally distributed and that it is uncorrelated with any other measures in

the model. We argue that our approach of utilizing a fixed effects strategy is preferable given that it avoids these assumptions.

[6] There was no evidence of collinearity problems introduced by including both the racial/ethnic composition measures and the racial/ethnic heterogeneity measure. Racial/ethnic heterogeneity was only correlated .45 with percent Asian, -.26 with percent white, .13 with percent African-American, and .04 with percent Latino. The VIF's of these measures were all less than 1.5.

[7] For instance, a neighborhood with an equal number of all groups will have the highest value on this measure $(1-(.2^2+.2^2+.2^2+.2^2+.2^2)=.8)$, whereas a completely homogeneous neighborhood will have a value of 0 $(1-(1+0+0+0+0)=0)$.

[8] To place the school district data into census tracts, we obtained shape files for school districts in 2000 from the Census Bureau website (www.census.gov) and intersected these with the shape files for 2000 census tracts. This allowed determination of the overlap in area between a given tract and a school district, and we weighted by area when placing the school district data into tracts.

[9] Adding a two-year lag did not show a significant effect in either home sales volatility model or the crime model. Thus, the findings do not appear sensitive to the choice of lag length.

[10] These covariances were constrained to have equal values over time points. Such an assumption is reasonable because we have no theoretical rationale to expect the values of these covariances to change over time.

[11] These within time covariances were constrained to be equal over time points because we had no theoretical rationale to expect their values to change over time. Nonetheless, these covariances between construct disturbances within time points were not empirically necessary in this model given their insignificant values.

[12] We explored additional break points other than the mean and generally found similar results. Given the conceptual clarity of the mean—and the fact that the effects were slightly stronger at this particular point—we chose this break point for the spline. In models estimated with a traditional interaction (without the splines), we also discovered a significant interaction. The right hand side of the figure of the plotted values looked similar to Figure 3 using the spline model (though the effect was a little weaker). However, the left hand side of the figure revealed the implausible conclusion that racial/ethnic heterogeneity *reduced* the amount of home sales volatility in a low crime tract. The spline model reveals that this unexpected effect was obtained because the linear model was actually a misspecification, and the strong positive effects at higher crime rates affected the slope of the line for low crime rates in the traditional linear interaction model. The spline models were estimated on just the equation with home sales volatility as the outcome (given that including these two spline measures of violent crime, along with the overall violent crime rate, in the full model would induce perfect collinearity).

[13] As an additional check of the robustness of our estimates to collinearity, we estimated ancillary models in which we collapsed four of our predictor variables into a factor of concentrated disadvantage—percent in poverty, percent divorced households, population density, and home values (negative loading)—and we collapsed three of our predictor variables into a factor of residential stability—average length of residence, percent owners, percent occupied units. These two factors were discovered by an exploratory factor analysis of these seven measures. The pattern of results for our variables of interest in these models was very similar to those of the main models, increasing confidence in our reported results (results available upon request).

[14] The fact that both of these coefficients have values less than one is consistent with an appropriate model specification. Values greater than one imply an explosive system (Bollen, 1989). It is notable that a preliminary model estimated without the time-lagged spatial lag of previous year home sales in the instability model showed a coefficient greater than one for this autoregressive parameter. This is further evidence of the appropriateness of taking into account this time-lagged spatial lag effect.

[15] Of course, the lagged outcome measure is explaining a large proportion of this variance.

[16] This is computed as follows: the average tract over this time period had a home sales volatility rate of 4.6. A one unit increase in violent crime increases this rate .14 units, or .14 / 4.6 = .03, or 3 percent.

[17] We also estimated a model that did not include the measure of residential stability in the tract in 1990 to assess whether including this measure in the model is affecting the effects of our one-year time lags. The results of this ancillary model were very similar to those presented here, lending confidence to the results.

[18] Although it might appear that higher rates crime have a slightly negative effect on home sales volatility in racially homogeneous tracts (based on the right hand side of figures 3 and 4), it should be emphasized that: 1) the slope of this spline is not significantly different than zero, and 2) there is just one tract that is simultaneously at least one standard deviation above the mean on violent crime and one standard deviation below the mean on racial/ethnic heterogeneity (suggesting the inadvisability of interpreting this slope too strictly). Indeed, there are only 13 tracts that are simultaneously even one-half standard deviation above and below the means of these two measures respectively.

Tables and Figures

Table 1. Summary statistics of variables used in analyses of tracts in Los Angeles, 1992-97. N=600 tracts at 6 time points.

	Mean	Std. Dev.
Logged violent crime per 10,000 population, 1992	5.118	0.852
Logged violent crime per 10,000 population, 1993	5.079	0.845
Logged violent crime per 10,000 population, 1994	4.971	0.835
Logged violent crime per 10,000 population, 1995	4.929	0.851
Logged violent crime per 10,000 population, 1996	4.828	0.883
Logged violent crime per 10,000 population, 1997	4.736	0.876
Logged property crime per 10,000 population, 1992	6.409	0.546
Logged property crime per 10,000 population, 1993	6.344	0.529
Logged property crime per 10,000 population, 1994	6.269	0.497
Logged property crime per 10,000 population, 1995	6.230	0.514
Logged property crime per 10,000 population, 1996	6.110	0.548
Logged property crime per 10,000 population, 1997	5.949	0.540
Percent home sales, 1992	3.733	1.963
Percent home sales, 1993	3.775	2.022
Percent home sales, 1994	4.632	2.237
Percent home sales, 1995	4.636	2.518
Percent home sales, 1996	5.189	2.797
Percent home sales, 1997	5.658	2.985
Socio-demographic census measures, 1990		
Proportion white	0.450	0.333
Proportion Asian	0.087	0.086
Proportion African-American	0.137	0.224
Proportion Latino	0.321	0.256
Proportion other race	0.005	0.005
Ethnic heterogeneity	0.435	0.160
Median home value (in $1,000,000's)	0.258	0.125
Proportion at/below 125% of poverty	0.199	0.141
Proportion divorced	0.284	0.131
Average length of residence	10.080	2.738
Proportion occupied units	0.944	0.030
Proportion owners	0.491	0.244
Population density (per .001 sq kilometer)	0.043	0.027

Table 2. Determinants of violent and property crime rates and home sales in tracts in Los Angeles, 1992-97. Cross-lagged models, including spatially lagged measure of temporally lagged outcome

	Model 1: violent crime model		Model 2: property crime model	
	(1)	(2)	(3)	(4)
	Violent crime	Home sales	Property crime	Home sales
Crime in previous year	0.920 **	0.140 **	0.975 **	0.127 **
	(106.49)	(4.12)	(156.80)	(3.34)
Percent home sales in previous year	-0.001	0.976 **	-0.001	0.973 **
	-(0.88)	(69.24)	-(0.77)	(68.03)
Outcome measure in neighboring tracts in previous year	0.028 **	0.064 **	-0.015	0.065 **
	(3.07)	(5.50)	-(1.78)	(5.56)
Socio-demographic census measures, 1990				
Percent Asian	-0.082	-0.735 **	0.012	-0.745 **
	-(1.69)	-(3.10)	(0.35)	-(3.10)
Percent African-American	-0.037	-0.271	-0.018	-0.084
	-(1.19)	-(1.82)	-(0.83)	-(0.58)
Percent Latino	0.021	-0.497 **	0.006	-0.344 *
	(0.77)	-(3.64)	(0.29)	-(2.51)
Percent other race	0.898	1.562	-0.112	1.756
	(1.32)	(0.47)	-(0.22)	(0.52)
Ethnic heterogeneity	0.079 **	0.282 *	-0.039	0.364 **
	(2.82)	(2.02)	-(1.87)	(2.62)
Median home value	-0.148 **	0.637 **	0.005	0.587 **
	-(3.27)	(2.82)	(0.14)	(2.58)
Percent at/below 125% of poverty	0.050	0.721 **	0.062	0.807 **
	(0.94)	(2.75)	(1.57)	(3.07)
Percent divorced	0.069	0.038	-0.017	0.044
	(1.07)	(0.12)	-(0.36)	(0.14)
Residential stability	-0.001	-0.027 **	-0.003 *	-0.026 **
	-(0.41)	-(2.94)	-(1.99)	-(2.81)
Percent occupied units	0.224	0.983	0.141	1.142
	(1.76)	(1.59)	(1.49)	(1.83)
Percent owners	-0.126 **	0.368 *	-0.004	0.338 *
	-(4.12)	(2.47)	-(0.16)	(2.23)
Population density	-0.379 *	2.010 *	-0.150	2.262 *
	-(2.05)	(2.23)	-(1.07)	(2.45)
School graduation rate	-0.156	-1.291	-0.321	-1.289
	-(0.26)	-(0.42)	-(0.72)	-(0.41)
R-squared	0.875	0.662	0.885	0.663

*** p < .01(two-tail test), * p < .05 (two-tail test). T-values in parentheses. N = 600 tracts at 6 time points.*

Table 3. Determinants of home sales in tracts in Los Angeles, 1992-97. Violent and property crime splines with break at mean value of crime. Including interaction between ethnic heterogeneity and high crime, ethnic heterogeneity and low crime, and between ethnic heterogeneity and percent home sales.

	(1)	(2)
	Home sales predicted by violent crime	**Home sales predicted by property crime**
Percent home sales in previous year	0.987 **	0.979 **
	(63.72)	(59.42)
Ethnic heterogeneity	-0.704	-1.288
	-(0.65)	-(0.45)
Below average crime in previous year	0.105 *	0.219 *
	(2.34)	(2.43)
Above average crime in previous year	0.005	-0.005
	(0.06)	-(0.08)
Ethnic heterogeneity X low crime	0.185	0.277
	(0.82)	(0.58)
Ethnic heterogeneity X high crime	1.056 **	0.706 *
	(3.62)	(2.23)
Ethnic heterogeneity X Percent home sales	-0.049	-0.048
	-(1.16)	-(1.08)

** p < .01(two-tail test), * p < .05 (two-tail test). T-values in parentheses. N = 600 tracts at 6 time points.
Equation also includes all socio-demographic census variables from Table 2 and spatially lagged home sales.

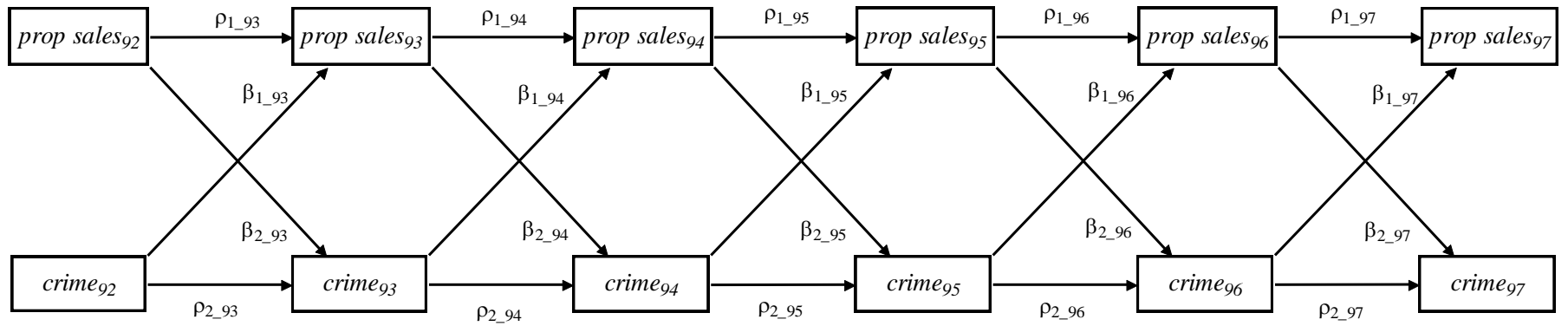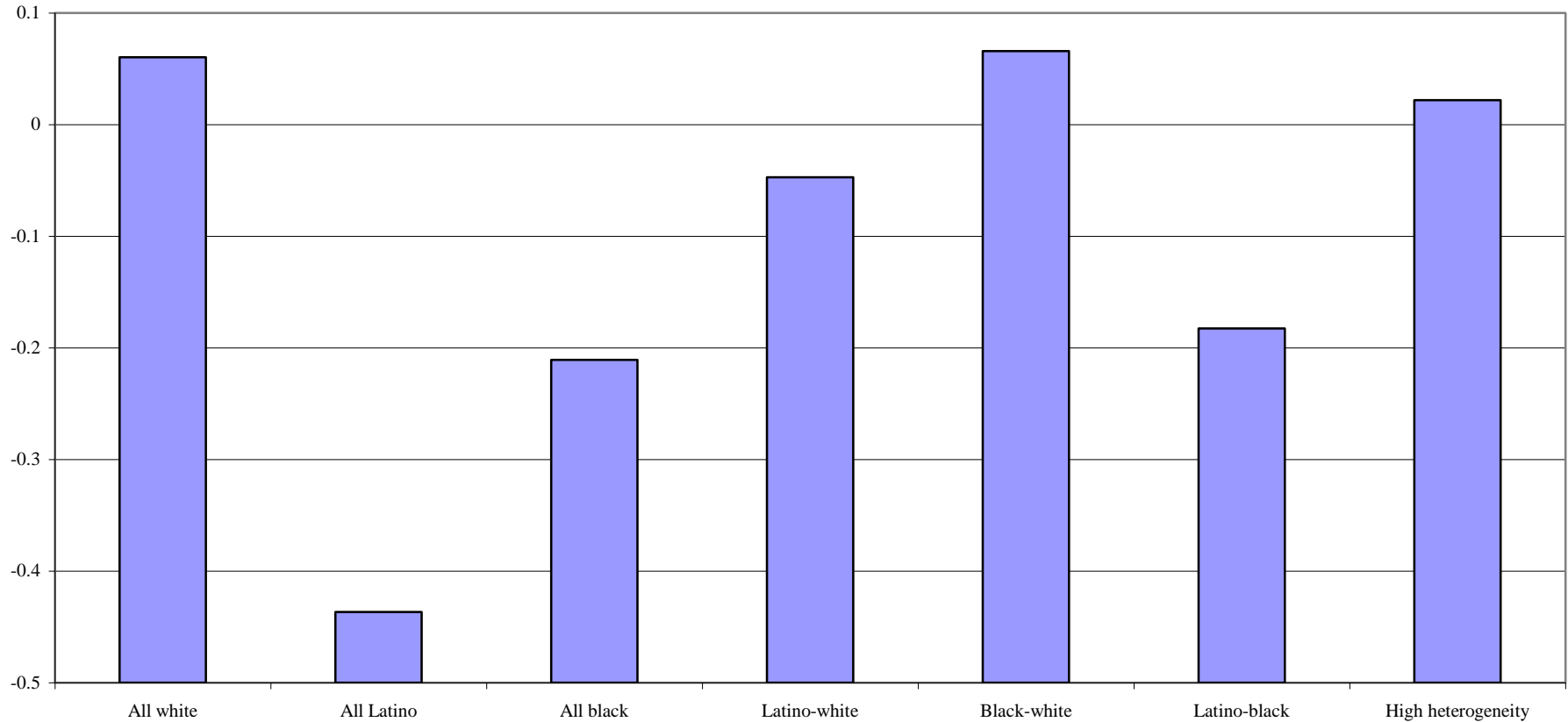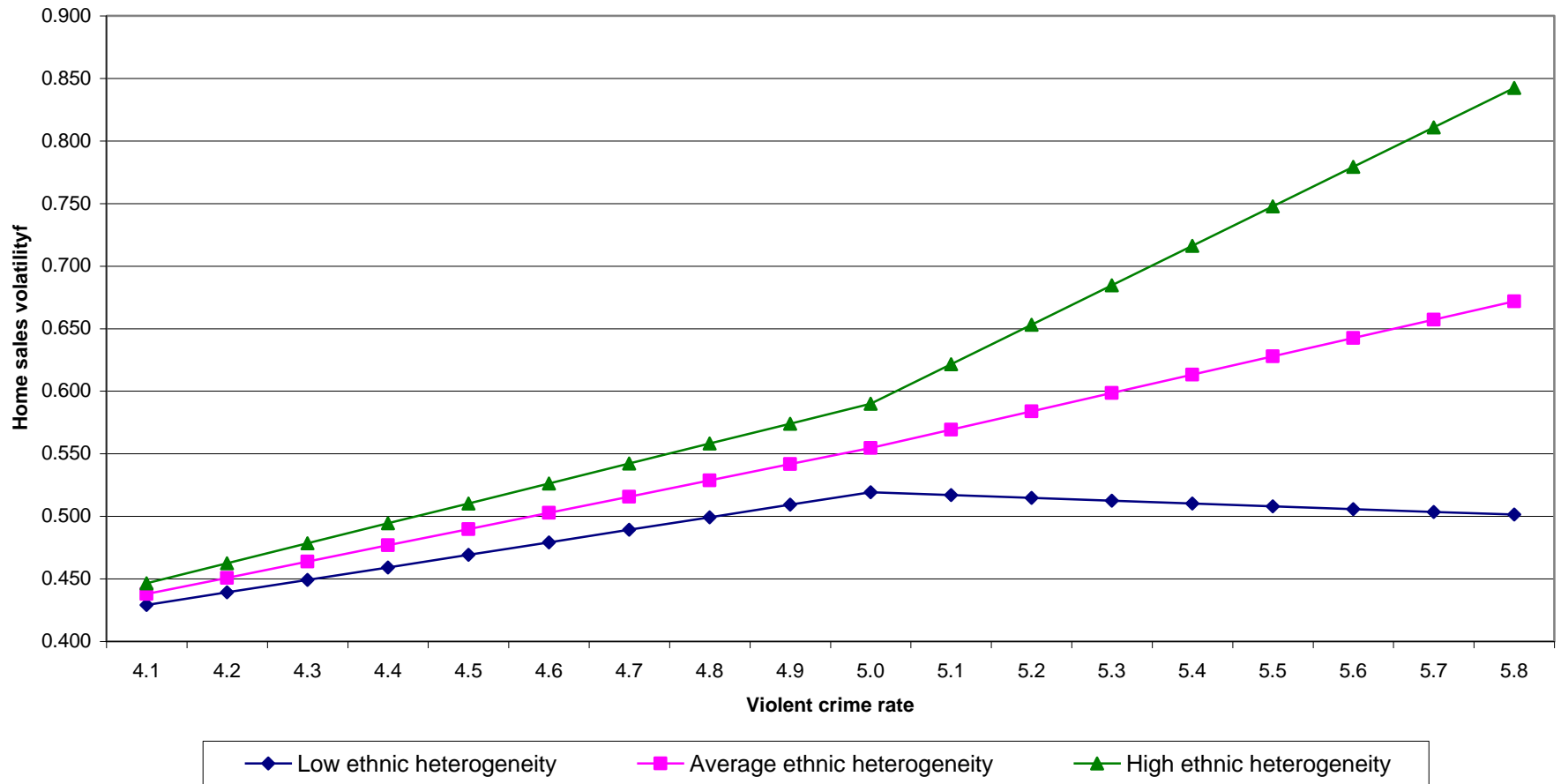Figure 1. Six time points- crime and property sales cross-lagged model

Figure 2. Marginal effect of tract racial/ethnic composition on home sales volatility
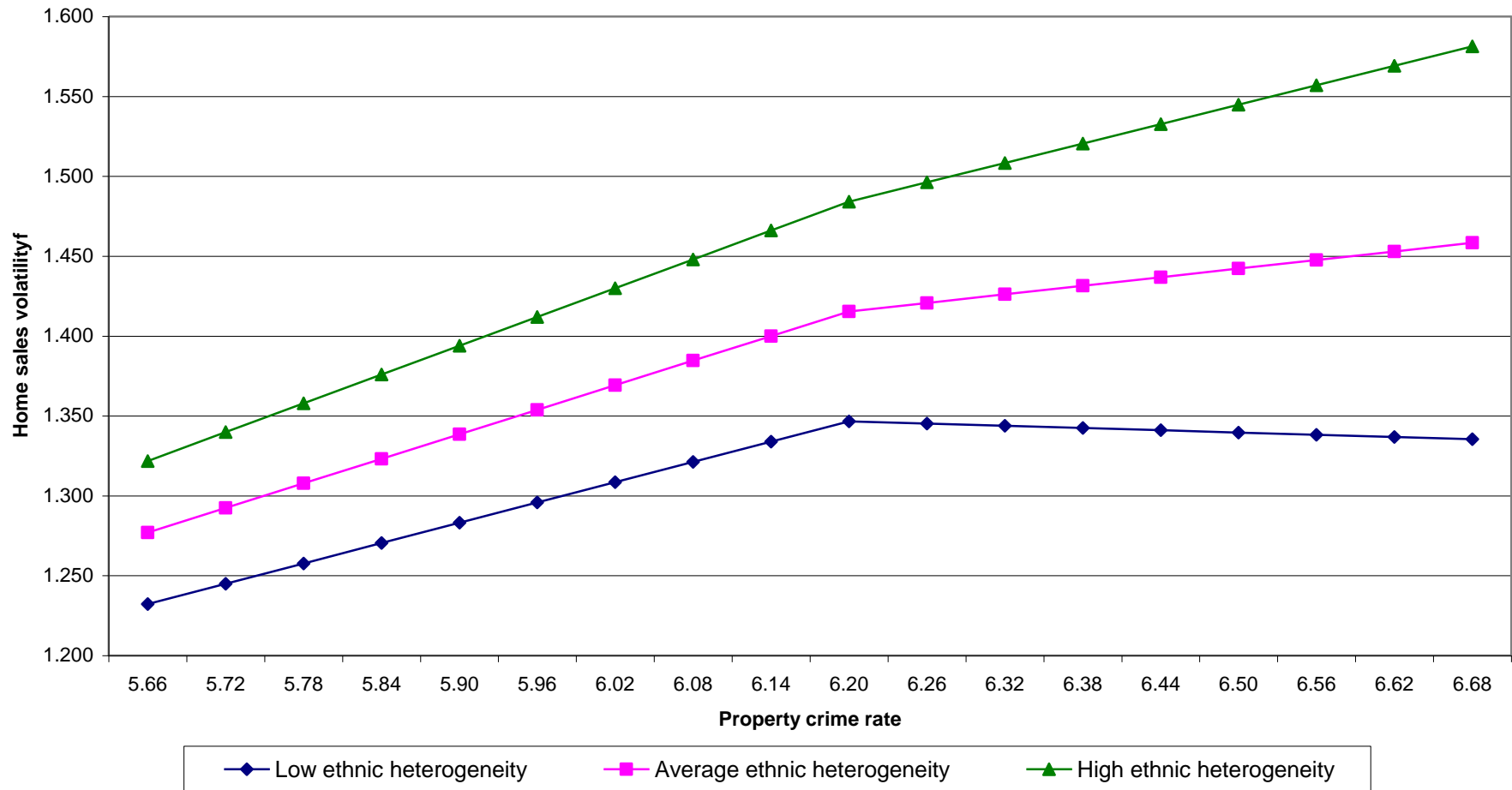

Note: "marginal effect" refers to the level of change in home sales volatility for a neighborhood with a particular racial/ethnic composition compared to a neighborhood with the average racial/ethnic composition of the sample. The neighborhood racial/ethnic compositions are: 1) 100% white, 2) 100% Latino, 3) 100% African-American, 4) half white and half Latino, 5) half white and half African-American, 6) half Latino and half African-American, 7) a high heterogeneity tract matching the proportions of one of the empirically most heterogeneous tracts in the sample

Figure 3. Marginal effect of violent crime on home sales volatility, moderated by ethnic heterogeneity. Spline model of violent crime effect.

Note: Note: "marginal effect" refers to the level of change in home sales volatility as the level of violent crime changes in tracts with ethnic heterogeity one standard deviation below the mean, at the mean, and one standard deviation above the mean.

Figure 4. Marginal effect of property crime on home sales volatility, moderated by ethnic heterogeneity. Spline model of property crime effect.

Note: Note: "marginal effect" refers to the level of change in home sales volatility as the level of property crime changes in tracts with ethnic heterogeity one standard deviation below the mean, at the mean, and one standard deviation above the mean.

Appendix

Table A1. Determinants of violent crime rates and home sales in tracts in Los Angeles, 1992-97. Including spatial effect of Percent of home sales in neighboring tracts in previous year

	Model 1			Model 2		
	(1)	(2)		(3)	(4)	(4)
	Violent crime	Home sales	Logged home values	Property crime	Home sales	Logged home values
Logged home values in previous year			0.841 ** (77.81)			0.844 ** (78.38)
Crime in previous year	0.920 ** (106.54)	0.138 ** (4.10)	-0.016 ** -(2.94)	0.975 ** (156.80)	0.127 ** (3.34)	-0.007 -(1.10)
Percent home sales in previous year	-0.001 -(0.81)	0.978 ** (70.01)		-0.001 -(0.77)	0.973 ** (68.03)	
Outcome measure in neighboring tracts in previous year	0.028 ** (3.07)	0.063 ** (5.49)	-0.001 -(0.21)	-0.015 † -(1.78)	0.065 ** (5.56)	(0.00) (0.18)

** p < .01(two-tail test), * p < .05 (two-tail test), † p < .05 (one-tail test). T-values in parentheses. N = 600 tracts at 6 time points. Equations also includes all socio-demographic census variables from Table 2.

Notes

[1] Violent crimes include robberies, aggravated assaults, and murders. Property crimes include burglaries, motor vehicle thefts, and larcenies.

[2] Although it is advisable to estimate negative binomial regression models when the count outcomes are relatively rare, our aggregated measures of violent and property crime have relatively large means such that the distribution approximates a normal distribution. Therefore, little would be gained by estimating a model treating the outcome with a Poisson distribution rather than the normal distribution.

[3] Dataquick, Inc. is a major supplier of real estate data that compiles information on housing transactions that were originally acquired from the Los Angeles County Recorder's Office. The data include single-family homes and condominium units sold to owner-occupiers (mobile homes and rental units are excluded).

[4] The outcome measure was the logged sales price of the unit. We included the following housing unit measures in the model: logged square footage of the unit; logged square footage of the lot; the logged number of bedrooms; the logged number of bathrooms; an indicator for the presence of a swimming pool; an indicator of whether the unit has a garage; the age of the unit; squared age of the unit (to capture nonlinear effects); and indicators of the season of the sale. The logged form of specific measures was used given that it resulted in a better prediction of the logged sale price.

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[7] For instance, a neighborhood with an equal number of all groups will have the highest value on this measure $(1-(.2^2+.2^2+.2^2+.2^2+.2^2)=.8)$, whereas a completely homogeneous neighborhood will have a value of 0 $(1-(1+0+0+0+0)=0)$.

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[16] This is computed as follows: the average tract over this time period had a home sales volatility rate of 4.6. A one unit increase in violent crime increases this rate .14 units, or .14 / 4.6 = .03, or 3 percent.

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