Title
The role of crime in housing unit racial/ethnic transition

Journal
Criminology, 48(3)

Author
Hipp, John R

Publication Date
2010

Peer reviewed

The role of crime in housing unit racial/ethnic transition

John R. Hipp*

March 25, 2010

Post-print. Published in Criminology 2010 48(3): 683-723

Word count (text): 8,920

Running Head: "Crime causes racial/ethnic transition"

* 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, 2367 Social Ecology II, Irvine, CA 92697; email: john.hipp@UCI.edu.

Bio

John R. Hipp is an Associate Professor in the department 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*.

The role of crime in housing unit racial/ethnic transition

Abstract

Previous research frequently observes a positive cross-sectional relationship between racial/ethnic minorities and crime and generally posits that this relationship is entirely due to the effect of minorities on neighborhood crime rates. This study posits that at least some of this relationship might be due to the opposite effect: neighborhood crime increases the number of racial/ethnic minorities. This study employs a unique sample (the American Housing Survey neighborhood sample) focusing on housing units nested in micro-neighborhoods over three waves from 1985 to 1993. This allows us to test and find that such racial/ethnic transformation occurs due to two effects: first, white households that perceive more crime in the neighborhood, or that live in micro-neighborhoods with more commonly perceived crime, are more likely to move out of such neighborhoods. Second, whites are significantly less likely to move into a housing unit in a micro-neighborhood with more commonly perceived crime, whereas African American and Latino households are *more* likely to move into such units.

The role of crime in housing unit racial/ethnic transition

One consistent finding of prior research is that neighborhoods and cities with a higher proportion of racial/ethnic minorities tend to have higher levels of crime (Krivo and Peterson, 1996; McNulty, 2001; Ouimet, 2000; Roncek, 1981; Roncek and Maier, 1991). Despite the almost exclusive focus on cross-sectional data in these studies, researchers usually conclude from this evidence that the presence of racial/ethnic minorities leads to more crime. The reasons given for such a relationship are numerous: from a culture of violence theory in which African Americans are posited to be inherently more violent (Wolfgang and Ferracuti, 1967), to a structural cultural explanation in which neighborhoods with high levels of poor racial/ethnic minorities lack the economic resources and social institutions to provide the social control that would otherwise reduce the level of crime (Sampson and Wilson, 1995), to a structural explanation that economic dislocation and unemployment in minority-dominant neighborhoods leads to an increase in the number of broken households and a subsequent decrease in the ability to provide social control that would otherwise reduce the amount of crime (Sampson, 1987). Nonetheless, a commonality in such theories is their assumption that the causal direction runs from the presence of minority residents to more crime. Given that these are almost exclusively cross-sectional studies, this assumption is generally neither questioned nor can it easily be tested.

Fewer studies have asked whether in fact this process may at least in part work in the opposite causal direction. That is, could higher levels of crime in neighborhoods cause an increase in the proportion of minority residents residing there? If in fact the causal direction is, at least in part, reversed, prior research employing cross-sectional data has overestimated the size of the effect if it assumes that the relationship is entirely due to the effect of racial/ethnic minorities on crime rates. The voluminous segregation literature (Farley and Frey, 1994;

Fischer, Stockmayer, Stiles, and Hout, 2004; Massey and Denton, 1987; Massey and Denton, 1993; Van Valey, Roof, and Wilcox, 1977) as well as the literature showing differential access to neighborhoods based on race/ethnicity due to steering and discriminatory behavior (South and Crowder, 1997a; South and Crowder, 1997b; Turner, Ross, Galster, and Yinger, 2000) suggests a potential mechanism through which crime in neighborhoods might change the racial/ethnic composition of the neighborhood. As elaborated in more detail below, to the extent that households wish to avoid neighborhoods with higher levels of crime, and to the extent that racial/ethnic minorities have constrained choices when selecting a neighborhood in which to move, neighborhoods with more crime may experience an increase in racial/ethnic minorities over time.

It is not entirely novel to suggest that crime may affect the racial/ethnic composition of a neighborhood, as scholars have occasionally raised this possibility (Bursik, 1986; Schuerman and Kobrin, 1986; Skogan, 1990; Taylor, 1995). Nevertheless, few studies have rigorously addressed this question. For instance, whereas two studies viewing the relationship between crime rates and racial/ethnic composition of cities over time are suggestive of such a relationship (Liska and Bellair, 1995; Liska, Logan, and Bellair, 1998), measuring this process at the level of the city is too crude a measure to precisely test whether this neighborhood-level process is present. Studies using neighborhood-level aggregated data are more appropriate, though they cannot determine whether this process represents disproportionate out-mobility, in-mobility, or both (Bursik, 1986; Morenoff and Sampson, 1997). Instead, I suggest that this is a multilevel question in which crime in a neighborhood might affect the household mobility decisions of people living in the neighborhood, as well as those considering *moving into the neighborhood*. This latter point raises an important question: if crime indeed changes the racial/ethnic composition of an area due to differential access to neighborhoods by race/ethnicity, does this neighborhood change occur due to differential ability to leave the neighborhood, or differential likelihood of entering the neighborhood?

The current study exploits a unique sample design to explore two key questions: 1) what effect does the common perception of crime in a micro-neighborhood have on the relative likelihood of whites and racial/ethnic minorities for moving out of a housing unit, and 2) what is the relative likelihood of whites and racial/ethnic minorities moving into a housing unit in a micro-neighborhood with a higher common perception of crime? Thus, although this study is limited to measuring micro-neighborhood crime based on the perceptions of residents, it has the advantage of being able to drill down to the housing unit in viewing mobility in and out of a unit. Furthermore, these perceptions of the crime context are measured at the level of the local micro-neighborhood, which provides advantages when studying these processes. Prior work aggregating crime measures to larger units of analysis has not obtained such geographic precision.

Residential transition

Does racial/ethnic composition affect the crime rate?

Considerable prior scholarship has explored the cross-sectional relationship between the presence of racial/ethnic minorities and the amount of crime in a city (Baumer, Lauritsen, Rosenfeld, and Wright, 1998; Chamlin and Cochran, 1997; Miethe, Hughes, and McDowall, 1991), and this relationship measured at the geographic level of neighborhoods (Hipp, 2007a; Krivo and Peterson, 1996; McNulty, 2001; Ouimet, 2000; Roncek, 1981; Roncek and Maier, 1991). These studies commonly assume that the presence of racial/ethnic minorities in the particular geographic unit gives rise to the higher levels of crime and disorder. One reason given for such a relationship in an early body of research in the social disorganization tradition was that the presence of minorities increased the level of racial/ethnic heterogeneity in a neighborhood, which reduced the number of social contacts between residents, leading to a subsequent reduced ability to provide the sort of informal social control that would otherwise address problems of disorder and crime (Shaw and McKay, 1942). More recently, researchers have pointed out that the presence of minorities themselves are not necessarily an indicator of heterogeneity, as neighborhoods that become populated almost entirely by one racial/ethnic minority group are actually quite homogeneous (Hipp, 2007a; Roncek and Maier, 1991; Sampson and Groves, 1989; Warner and Rountree, 1997).

Other theories have however posited an even more direct effect from the presence of racial/ethnic minorities to the occurrence of crime and disorder. For instance, cultural theories such as the culture of violence perspective posit that there exists an African American culture that does not negatively sanction violent behavior as strongly as does mainstream culture, resulting in more violent behavior on the part of residents (Wolfgang and Ferracuti, 1967). Another perspective adopts a structural/cultural approach in arguing that the culture in minority-dominated neighborhoods is shaped by the larger structural system that brings about economic dislocation in these neighborhoods (Sampson and Wilson, 1995). That is, the exodus of middle-class minority residents from these neighborhoods eliminates positive role models espousing more conventional norms, and the remaining low-income minority residents develop a non-normative culture due to this structural imposition. Such neighborhoods are therefore populated with the truly disadvantaged, who lack the economic resources and time to support the neighborhood's institutions, and do not provide the type of role models that would increase neighborhood youths' desire to embrace middle-class values (Wilson, 1987). This isolation causes these neighborhoods to develop norms that accept the use of violence and crime.

Exiting high crime neighborhoods: differential ability?

Despite this dominant paradigm assuming that it is the presence of racial/ethnic minorities that brings about more crime, there is a small but growing literature suggesting that at least some of this relationship might occur because minority residents are pushed into such neighborhoods. To understand this perspective, first consider the possibility that crime in a neighborhood might induce residential mobility. Of course, this argument contradicts the social disorganization theory's postulate that residential instability leads to more crime.

The notion that neighborhood crime might induce residential mobility is not new, as scholars have occasionally suggested this possibility in recent years (Bursik, 1986; Schuerman and Kobrin, 1986; South and Messner, 2000; Xie and McDowall, 2008). Although this is hardly a controversial suggestion—clearly, most households wish to avoid neighborhoods with higher levels of crime—fewer studies have actually empirically tested this possibility. Nonetheless, the few studies exploring this question have provided some supportive evidence. For instance, a study using the National Crime Victimization Survey found that experiencing a crime event increased the likelihood of exiting a neighborhood (Dugan, 1999). A recent study with the same data found that victimization experienced by one's nearest four neighbors also increased residential mobility (Xie and McDowall, 2008). Skogan (1990) found for 40 neighborhoods that crime rates caused dissatisfaction and a desire to move. Likewise, a study of census tracts in Los Angeles found that tracts with higher levels of violent or property crime in one year experienced a higher volume of home sales the following year (Hipp, Tita, and Greenbaum, 2009). Studies using data aggregated to cities have found that higher levels of crime led to greater population loss over time (Cullen and Levitt, 1996; Sampson and Wooldredge, 1986), and that higher rates of violent crime in central cities relative to suburbs spurred city-to-suburb mobility and inhibited suburb-to-city moves (South and Crowder, 1997b).

Although it is clear why households might want to leave a neighborhood with high levels of crime, it is less clear why another household would be willing to *enter* such a neighborhood. One plausible explanation is that no households in fact wish to enter such neighborhoods, but rather that such movement is driven by an economic process.[1] That is, to the extent that low crime neighborhoods are more desirable, they will have higher rents and higher home values. As a consequence, only households with the greatest economic resources will be able to reside in such neighborhoods. On the other hand, an increase in crime will decrease the desirability of the neighborhood, pushing down rents and home values. Indeed, cross-sectional studies have found that neighborhoods with higher rates of crime have lower home values (e.g., Buck and Hakim, 1989; Schwartz, Susin, and Voicu, 2003; Thaler, 1978). There is also evidence that increasing crime in the neighborhood decreases home values (Tita, Petras, and Greenbaum, 2006), and that tracts with higher rates of crime in one year experience a relative decrease in home values the following year (Hipp, Tita, and Greenbaum, 2009).

This economic argument has implications for racial/ethnic minorities in neighborhoods. To the extent that such minorities have fewer economic resources in general, they will be disproportionately unlikely to leave such neighborhoods (Massey and Denton, 1985). This process implies that over time, a high crime neighborhood will not only increase the number of low income residents, but it will also increase the number of low income racial/ethnic minorities. As a consequence, high income white residents will disproportionately abandon the neighborhood. This suggests that there will be a change in the neighborhood's racial/ethnic composition due to the amount of crime and disorder. Of course, this argument implies that we should observe no difference in the race/ethnicity of those who leave in response to higher crime if the economic resources of neighborhood residents are taken into account.

Nonetheless, the legacy of segregation in the U.S. implies a possible explanation for why racial/ethnic minorities may have a constrained ability to leave an undesirable neighborhood beyond their limited economic resources, and underlies the place stratification theory. The highly segregated nature of racial/ethnic minority communities is well documented (Frey and Farley, 1996; Massey, Gross, and Shibuya, 1994; Massey and Hajnal, 1995), and the greater tendency for racial/ethnic minorities to enter neighborhoods dominated by members of their same race/ethnicity is also firmly established (Logan, Alba, and Leung, 1996; Massey and Mullan, 1984; Rosenbaum, 1994; Rosenbaum and Argeros, 2005; South and Crowder, 1997b). Thus, the place stratification theory posits that such mobility constraints limit the neighborhoods that racial/ethnic minorities can enter. Given that the number of neighborhoods dominated by minorities is far smaller than those dominated by whites, the implication is that racial/ethnic minorities face considerable constraints when choosing where to move. Indeed, evidence suggests that although racial/ethnic minorities express an equal desire to leave neighborhoods as whites (Lee, Oropesa, and Kanan, 1994), they in fact are less likely to do so (Boehm, Herzog, and Schlottmann, 1991; Deane, 1990).

What might be the mechanisms explaining such constrained choice for racial/ethnic minorities? There is no shortage of possible explanations as seen in the voluminous literature describing the role of gatekeepers, steering, and discriminatory behavior. Studies have shown that gatekeepers (such as real estate agents) are an important source of segregation as they often present racial/ethnic minority home buyers with a more limited number of neighborhoods (La Gory and Pipkin, 1981; Turner, Ross, Galster, and Yinger, 2000). In these instances, this steering pushes racial/ethnic minorities towards neighborhoods already highly populated with fellow group members, and away from white-dominated neighborhoods. Additionally, there is a large literature showing discriminatory behavior on the part of potential landlords and property management companies. For instance, audit studies have consistently shown that racial/ethnic minorities are often turned down from housing options despite identical credentials to white candidates (Turner, Ross, Galster, and Yinger, 2000). One study even found such evidence when conducting over-the-phone audits: in this instance, speaking in a black vernacular yielded fewer offered residences (Fischer and Massey, 2004). As a consequence, racial/ethnic minorities likely have fewer options when it comes to choosing a neighborhood in which to reside.

Due to these limited mobility options, a racial/ethnic minority household living in are area with increasing levels of crime may be unable to leave the neighborhood. That is, a white household may respond to increasing crime rates by abandoning the neighborhood. However, a racial/ethnic minority household may also wish to leave and proceed to engage in a search for an alternative neighborhood. If this search is constrained by the above mechanisms, they will be less likely to find a suitable alternative. As a consequence, the household may be less likely to leave given that the alternatives appear no better, and not because they are not concerned about the changes in the neighborhood.

Despite the plausibility of these hypotheses, we have limited empirical evidence testing whether whites have a differential ability to leave high crime neighborhoods compared to racial/ethnic minorities. Two studies employed city-level longitudinal data to test and find that higher levels of crime resulted in a greater concentration of nonwhite population in cities (Liska and Bellair, 1995; Liska, Logan, and Bellair, 1998). Another study measuring crime rates based on city-level crime rates actually found that African Americans in the central city were more likely than whites to move to a different tract in response to a higher ratio of city to suburb violent crime (South and Crowder, 1997b). Despite the importance of these studies, these results can only be suggestive given that the high level of aggregation precludes testing these processes at the more appropriate geographic level of housing units nested within local neighborhoods. One longitudinal study of Chicago census tracts found that the rate of homicide in the census tract led to a general population loss of *both* whites and African Americans (Morenoff and Sampson, 1997), which does not support the notion of disproportionate mobility, at least when measured aggregated to census tracts. Another study of neighborhoods in Chicago did find that the delinquency rate in 1960 increased the number of non-whites in 1970 (Bursik, 1986). This is suggestive evidence, although the focus on a single city forty years ago, along with the small number of control variables, leaves open the question of whether we might observe such a process with more recent data focusing on transition in the actual housing unit.

Who is moving in?

The above discussion implies a second consideration: not only may racial/ethnic minorities be less likely to leave a high crime neighborhood, but they may also be more likely *to enter* a high crime neighborhood. Similar to the process described earlier regarding residential mobility out of the neighborhood, if racial/ethnic minorities have a constrained choice on where to move, they may be more likely to move into a neighborhood with higher levels of crime. That is, the household will have fewer neighborhoods to choose from when deciding on a new residence, and as a consequence may be forced to consider neighborhoods with more crime. Crime would not necessarily be desirable, of course, but such households may simply have few other options in neighborhoods to consider. This implies that racial/ethnic minorities will be more likely than whites to move into neighborhoods with more crime.

It is an empirical question whether either, or both, of these two processes regarding out-mobility and in-movement are at work. Both can affect the neighborhood's racial/ethnic composition. For instance, a neighborhood would experience a racial/ethnic transition if racial/ethnic minorities are less likely to leave a high crime neighborhood even though the racial/ethnic composition of the entering households does not change. It can be easily shown that over time this will lead to a change in the racial/ethnic composition of the neighborhood. Alternatively, a neighborhood would also experience a racial/ethnic transition if racial/ethnic minorities are no more likely to leave a high crime neighborhood than whites but racial/ethnic minorities are more likely *to enter* the neighborhood. A third possibility is that both of these processes are at work—whites are more likely to leave a high crime neighborhood and racial/ethnic minorities are more likely to enter it—which would lead to the most rapid transformation of the neighborhood's racial/ethnic composition.

It is instructive to note that about thirty years ago Aldrich and colleagues (Aldrich and Reiss, 1976; Aldrich, Zimmer, and McEvoy, 1989) studied an analogous question when asking whether a transformation of the racial/ethnic composition of a neighborhood's residents leads to a change in the racial/ethnic composition of the business owners. Studies from both the U.S. (Aldrich, Zimmer, and McEvoy, 1989) and Britain (Aldrich and Reiss, 1976) found that although white business owners were no more likely to abandon such a neighborhood, white business owners were far less likely *to enter* such neighborhoods. Thus, the racial/ethnic composition of the business owners in such neighborhoods changed over time due to this differential likelihood of entering the neighborhood. Such a finding is important for understanding the process through which such change occurs, and allows more appropriate policy interventions.

Likewise, in the present study, whereas an important first question is whether a neighborhood with higher levels of crime is more likely to transition to a higher proportion of racial/ethnic minorities, an equally crucial second question is how this transition takes place? If it occurs because whites are more likely to abandon such neighborhoods, that will imply a need to focus on the differential ability of racial/ethnic minorities to leave such neighborhoods. If it occurs because racial/ethnic minorities are more likely to *enter* such neighborhoods, that will imply a different set of policy choices in response.

Nevertheless, we have little information on whether racial/ethnic minorities are disproportionately likely to move into or out of higher crime neighborhoods. Studies finding that higher crime neighborhoods have more racial/ethnic minorities over time (Bursik, 1986) are unable to determine whether this occurs due to an increased likelihood of whites abandoning such neighborhoods or due to an increased likelihood of racial/ethnic minorities entering such neighborhoods. Testing for in-mobility requires a sample that follows housing units over time—as employed here—rather than households.

Summary

The present study asks whether higher levels of commonly perceived crime lead to a transformation in the racial/ethnic composition of the neighborhood. This study provides three important contributions to the literature: 1) by focusing on housing units, it is able to avoid the challenges inherent in aggregating residential mobility measures to larger geographic units such as census tracts, given that such change must occur at the level of the housing unit; 2) the study design of following housing units over time allows assessing the degree to which any change occurs due to the disproportionate likelihood of whites leaving such neighborhoods or the disproportionate likelihood of racial/ethnic minorities entering such neighborhoods; 3) by measuring crime based on the perceptions of residents in the immediate area (as measured by the eleven closest housing units) it provides a more geographically precise estimate of the crime environment experienced by the housing unit rather than crime measures aggregated to the level of a census tract or even larger geographic unit. Furthermore, I can assess the extent to which a household's own perception of neighborhood crime translates into mobility.

Data and Methodology

Data

The sub-sample of the American Housing Survey (AHS) employed here is uniquely suited to address these research questions. This special neighborhood sub-sample of the AHS initially randomly selected 680 housing units in 1985 from the full AHS that were located in either urban or suburban locations, and then interviewed the ten closest neighbors of the initial respondent.[2] In what follows, I refer to these eleven households as a "micro-neighborhood." This unique data set thus has *housing units* nested within micro-neighborhoods as the units of analysis, allowing testing whether the structural characteristics of the local micro-neighborhood affect residential housing transition. Only micro-neighborhoods with at least 5 respondents were included, thus there were 663 micro-neighborhoods in 1985. There are three waves of data that follow these housing *units* over time. At each wave of data collection, interviewers returned to the exact same housing units, thus there is not attrition in this sample design, but only possible nonresponse (as discussed below). Furthermore, to account for new housing developments, the samples in 1989 and 1993 were augmented with new micro-neighborhoods. Thus, information from 1985 is used to predict the likelihood of the household leaving by 1989 and the new household's characteristics in 1989, and information from 1989 is used to predict the likelihood of the household leaving by 1993 and the new household's characteristics in 1993. As a consequence, there is a sample of 6,865 units for the in-mobility models (units that changed residents over one of these two periods), and samples of 1,172 Latino residents, 2,032 African American residents, and 11,590 white residents in the two waves in the residential mobility models.[3]

Outcome measures

One outcome measure is an indicator of whether a new household lived in the unit four years later (showing outward residential mobility). A new household is defined as one with a new household head: it is not considered mobility if only sub-members of the household leave between the two waves.[4] The other three outcome measures are the race/ethnicity of the household head of the new household residing in a residence four years later. These measures indicate whether or not the household is white, African-American, or Latino. In the relatively rare cases in which a household did not participate in a survey, this missing data is treated using a multiple imputation strategy, described below.

Crime causes racial/ethnic composition

Crime in the environment

I measure crime in the local environment by combining the reported perceptions of the eleven households in the micro-neighborhood. This is therefore measuring the *common perception of crime* of these residents. The AHS asks respondents a series of three questions about crime in the neighborhood (as defined by the respondent): is crime a problem, is it so much of a problem that it's a bother, and is it such a bother that the respondent wishes to move. These questions are nested, as a respondent was only asked the latter questions if they answered the previous questions affirmatively. These responses were combined into a four point response in which the respondent either replies "no" to all questions, replies "yes" to one, "yes" to two, or "yes" to all three. I accounted for likely measurement error in these responses by estimating this as a micro-neighborhood-level latent variable of common perception of crime, as described below in the methods section. Given the theorizing and evidence from prior research that residents' perceptions of crime or disorder may be just as important for affecting behavior as more objective measures (Deane, 1990; Sampson, 2009; Sampson and Raudenbush, 2004), this household-level perception of crime measure was also included in the residential mobility models to test whether it affects mobility beyond this micro-neighborhood-level effect.[5]

Of course, measuring crime is always a challenging task and no perfect measure exists of the construct. Although studies often measure crime based on official crime reports, the naïve assumption that official crime rates are infallible has long since given way to the acknowledgement that there is a considerable amount of underreporting for such official statistics. For instance, the 2005 National Crime Victimization Survey reported that only 62 percent of aggravated assaults, 60 percent of robberies, and 56 percent of burglaries were reported to the police (Klaus and Maston, 2006). A second approach, victimization studies, has desirable properties; however, these require large samples to get reasonably useful estimates of crime in small geographic areas. Furthermore, they do not capture crimes experienced by victims *not living* in the neighborhood. A third approach—measuring crime based on the reported perceptions of residents—is potentially fallible as well given the possible systematic biases of certain types of households when assessing this.

Despite the imperfections of different measures of crime, there is some evidence that these measures may not be as bad as some have assumed. For instance, one study found that perceptions of crime can map on quite reasonably to official crime rates (Perkins, Meeks, and Taylor, 1992). Another exhaustive study used seven waves of data over a 25-year period and found a relatively high correlation (about .70) between the official violent crime rate in a census tract and residents' combined perceptions of crime (Hipp, 2007b). It should be noted that even this may be an underestimate given the aggregation to census tracts, which may experience heterogeneity in the amount of crime across the blocks *within* a tract. Another study demonstrated criterion validity for three measures of crime, finding that the structural measures in their model had very similar effects regardless whether they measured the outcome of crime by the official crime rate, victimization reports, or the common perception of crime (Sampson, Raudenbush, and Earls, 1997). Furthermore, given that I am combining the reports of eleven households living adjacent to one another, rather than combining the reports of residents scattered throughout a census tract, I argue that this is a more geographically precise estimate of the amount of crime. Studies using measures of crime aggregated to census tracts implicitly make the rather strong assumption that the rate of crime is constant across all of the blocks in a census tract.

I also point out that for the analyses viewing the characteristics of residents moving into the neighborhood that it is residents who lived in the neighborhood four years previously who are assessing the level of crime. The new residents' perceptions of crime are immaterial to this measure, and thus cannot bias the results. Although the prior household's inaccurate perception of more crime in the neighborhood may increase the likelihood that they will leave (and indeed this possibility is explicitly accounted for in the models predicting the likelihood of exiting such housing units), there is little reason to suspect that such a household will systematically be replaced by a household of any given race/ethnicity.

Crime causes racial/ethnic composition

It is possible that households may use the racial/ethnic composition of the micro-neighborhood as a proxy for the amount of crime. For instance, Krysan (2002) suggested that whites often find mixed-race neighborhoods undesirable due to an inflated assessment of the amount of crime in such neighborhoods. However, while there is evidence that white residents who *perceive* a more racially mixed environment are more likely to fear crime (Chiricos, Hogan, and Gertz, 1997; Rountree, 1998), studies have often found no relationship between the actual racial/ethnic composition of the environment and whites' perceptions of crime (Chiricos, Hogan, and Gertz, 1997; Rountree, 1998). For instance, one study of residents in three cities found that white residents perceived more crime than African Americans in census tracts with more young African American males in Seattle, but no such effect was detected in the samples of Chicago and Baltimore (Quillian and Pager, 2001). However, the fact that this same study found that all residents (both black and white) perceived more crime in census tracts with more young black males suggests that perceptions may in fact be impacted by the racial/ethnic composition. Of course, given that studies have consistently shown that racial/ethnic heterogeneity is associated with higher levels of official rates of crime (Hipp, 2007a; Roncek and Maier, 1991; Sampson and Groves, 1989; Warner and Rountree, 1997), it is unclear whether residents' reports of more crime when living in racially/ethnically mixed neighborhoods are misperceptions, or are simply reflecting actual higher levels of crime. Given this possible bias, it is important to account for the racial/ethnic composition in the models.

Household and micro-neighborhood-level predictors

In the models predicting the race/ethnicity of the new residents, the race/ethnicity of the household at the previous time point was taken into account by creating indicators of whether the household was white, African-American, Latino, or other race. Given that the racial/ethnic composition of the micro-neighborhood affects its desirability and hence mobility behavior (Charles, 2000), measures of the percent white, African-American, Latino, and other race were created.

For the residential mobility model, I also included several household-level measures and individual-level measures (based on the characteristics of the household head) that are likely important predictors of mobility. A measure of the age of the respondent, measures of the number of children aged 0 to 5, aged 6 to 12, or aged 13 to 18 in the home, and dichotomous indicators for marital status (married, divorced, widowed, with single as the reference category) account for stage of the life course. I measured community investment with an indicator of whether the respondent owned their residence and a measure of the length of time in the residence (log transformed). To account for mis-match with the housing unit, a measure of the persons per room (log transformed) was created to capture over-crowding. SES effects were captured with measures of household income (logged) and years of education of the respondent.

In ancillary models I tested whether the household-level measures in the residential mobility model explained who moved into the unit at the next time point. As expected, nearly all of these measures were insignificant. The one exception was the measure of length of residence of the previous household. Given that it had a significant effect in certain models, and the fact that it is plausible to suppose that long-term residents may indeed be different in whom they transition the unit to, I left this measure in the in-movement models.

I also took into account several characteristics of the micro-neighborhood. The average household income in the micro-neighborhood accounts for economic resources. Residential stability is measured by the percentage of new households in the last five years, the percentage vacant units, and the percent homeowners in the micro-neighborhood. Given that crowding might affect who enters a neighborhood, a measure of the percent of households living in crowded conditions (more than one person per room) was constructed. Finally, a measure of the percent households with children, and an indicator of the wave of the survey were constructed. The summary statistics for the variables used in the analyses are shown in Table 1. I tested for and found no evidence of collinearity problems in the estimated models (all variance inflation values were below 4).

<<<Table 1 about here>>>

Methodology

Simply summing the perception of crime of residents in the micro-neighborhood would ignore the certain measurement error in these responses. I instead adopted an approach that explicitly accounts for this measurement error by estimating this as a latent variable of commonly perceived crime (for a detailed description of this approach, see Ludtke, Marsh, Robitzsch, Trautwein, Asparouhov, and Muthen, 2008). This equation is:

(1) $$x_{ik} = \Lambda_1 \xi_k + \varepsilon_{ik}$$

where x_{ik} is the combined four-point response in the AHS regarding the level of crime reported by the i-th respondent of I respondents in the k-th micro-neighborhood, ξ_k is the latent variable of common perception of crime in the micro-neighborhood, Λ_1 measures the impact of perceived crime on the respondent's report of crime (since the ordering of respondents in neighborhoods is random, these λ's are constrained equal), and ε_{ik} is a disturbance term (the variances of the ε's are constrained equal).[6] Such an approach was adopted by Bollen and colleagues in different substantive contexts (Bollen and Paxton, 1998; Speizer and Bollen, 2000), as well as Sampson and Raudenbush (1997) who used an IRT approach (which is identical to the approach here).[7]

To account for possible different mobility processes by race/ethnicity, I estimated the household residential mobility model as a multiple groups analysis in which the following equation is simultaneously estimated separately for whites, Latinos and African Americans:

(2) $$y_{ik(t+1)} = \beta_{\xi k}\xi_k + \Gamma_{Xik}X_{ik(t)} + \Gamma_{Xk}X_{k(t)} + \Gamma_{YR}YR$$

where $y_{ik(t+1)}$ is the probability that the household will move of the i-th respondent of I respondents in the k-th micro-neighborhood, ξ_k is the latent variable of neighborhood crime which has $\beta_{\xi k}$ effect on the outcome (the k-subscript makes explicit that this is measured at the micro-neighborhood level), X_{ik} is a matrix of independent variables with values for each household i in micro-neighborhood k (the i- and k-subscripts makes explicit that these are measured at the individual or household level), Γ_{Xik} shows the effect of these predictors on the probability of moving, X_k is a matrix of micro-neighborhood-level independent variables for micro-neighborhood k, Γ_{Xk} shows the effect of these predictors on the probability of moving, YR indicates which year of the sample the observation comes from and has a Γ_{YR} effect on the outcome. To account for the ordinal nature of the crime assessments by households (x_{ik}) and the dichotomous outcome of moving (y_{ik}), I created a polychoric correlation matrix and estimated the model using a diagonally weighted least squares estimator in the Mplus 4.1 software. This approach assumes that these ordinal measures have unobserved continuous measures underlying them that are normally distributed. This is analogous to simultaneously estimating each of these outcomes as probit or ordered probit equations. The clustering in the data was accounted for by correcting the standard errors using robust standard errors corrected for micro-neighborhood-level clustering.

For the models testing the characteristics of the household moving into the unit, the equation predicting that the new household is, for instance, white is:

(3) $$y_{ik(t+1)} = \beta y_{ik(t)} + \beta_{\xi k}\xi_k + \Gamma_{Xik}X_{ik(t)} + \Gamma_{Xk}X_{k(t)} + \Gamma_{YR}YR + \varepsilon_{ik(t)}$$

where $y_{ik(t+1)}$ is an indicator of whether or not the new household in the unit is white of the *i*-th respondent of *I* respondents who are new in the *k*-th micro-neighborhood, $y_{ik(t)}$ is a vector showing the race/ethnicity of the prior residents in the unit and has a vector of β effects on the outcome, ξ_k is the latent variable of neighborhood crime which has $\beta_{\xi k}$ effect on the outcome, X_{ik} is a matrix of independent variables with values for each individual *i* in micro-neighborhood *k*, Γ_{Xik} shows the effect of these predictors on the outcome, X_k is a matrix of micro-neighborhood-level independent variables for micro-neighborhood *k* and Γ_{Xk} shows the effect of these predictors on the outcome, YR indicates which year of the sample the observation comes from and has a Γ_{YR} effect on the outcome. For maximum efficiency, these three outcomes were estimated simultaneously in Mplus 4.1 using a diagonally weighted least squares estimator. To allow inferences to the entire sample, I accounted for non-movers by estimating a selection model in which the outcome is whether or not the household moved during the four year period. This probit selection model was estimated and the inverse Mills ratio from this selection model was included in the final models.[8] Missing data was addressed with a multiple imputation strategy (Rubin, 1987).[9] This approach requires the less stringent assumption of missing at random (MAR) rather than the missing completely at random (MCAR) assumption of listwise deletion. Five datasets were imputed, and the results were combined with appropriate standard errors using the standard formulas that account for the variability both within imputed datasets, and across datasets (Rubin, 1987; Schafer, 1997).[10]

Results

Residential mobility

I begin by focusing on the models predicting movement out of the neighborhood.[11] The model was estimated separately for white, African American, and Latino households. There is a differential likelihood by race/ethnicity of leaving a housing unit in an area with a higher common perception of crime. Model 1 in Table 2 shows strong evidence that white households are more likely to leave a neighborhood when they perceive more crime, and there is also a contextual effect in which they leave when there is a higher common perception of crime. A white household that perceives that crime is a problem is .045 more likely to leave the neighborhood than one that does not perceive a problem, and a one unit increase in commonly perceived crime in the local micro-neighborhood further increases the probability of moving .111 units. Thus, perceiving one unit more crime increases the predicted probability of moving 4% for whites (for a household at the mean on all other characteristics), and a one standard deviation increase in the micro-neighborhood common perception of crime increases it 5%.[12]

Deleted: with

Deleted: In addition to this contextual effect, a household that perceives more crime is even more likely to move out.

<<<Table 2 about here>>>

On the other hand, there is no evidence in models 2 and 3 in Table 2 that African Americans or Latinos are more likely to move out of a micro-neighborhood if they perceive more crime, or if there is a higher level of commonly perceived crime. We simply see no evidence that members of these two racial/ethnic minority groups are more likely to abandon a housing unit if they perceive more crime, or if the micro-neighborhood has higher reported levels of commonly perceived crime. Although there is evidence that whites are more likely to leave a micro-neighborhood in response to higher levels of commonly perceived crime, and a lack of evidence that Latinos and African Americans do so, the models lack the statistical power to distinguish between these different group effects. That is, whereas the model has the statistical power to determine that the effect of crime on white mobility is significantly different than zero, it lacks the power to conclude that the difference in the effect of crime on white mobility significantly differs from that on black or Latino mobility.[13] Note that statistical power alone is not the reason for this different conclusion for whites, as the estimated coefficients for the effect of crime on mobility for Latinos and blacks are much smaller than that estimated for whites. On the other hand, it is the case that the effect of the household's own perception of crime on residential mobility is significantly different between whites and these two minority groups.

Deleted: with

Deleted: Likewise, a specific Latino or African American household that perceives more crime is no more likely to act on that perception and move out of the housing unit.

I briefly note that the control variables in these models showed results consistent with prior literature. Residents who have lived longer in the residence are much less likely to move, and there is an additional contextual effect in which micro-neighborhoods with more new residents at one time point (residential instability) increase the likelihood that the household will move by the next time point. Another robust finding consistent with prior research is that homeowners are much less likely to move, regardless of their race/ethnicity. The presence of young children (less than 6 years of age) increases the likelihood of residential mobility for whites and African Americans, quite possibly in response to the need for quality schools.

Crime causes racial/ethnic composition

New household is white

I next turn to the in-mobility model. Focusing first on the equation predicting whether the new household in the unit four years later is white, there are the expected strong stasis effects for the race/ethnicity of the housing unit. Housing units that were occupied by nonwhite residents at time one are far less likely to have white residents move in four years later, as seen in equation 1 in Table 3. The coefficients for the different race/ethnicities suggest differing effects by race: the presence of an African-American household at the previous time point has the strongest negative effect on the likelihood that the new household will be white, whereas the presence of a Latino household at the prior time point has a strong, though slightly weaker, negative effect, and the presence of other race households does not have a significantly negative effect. The presence of an African American household at the prior time point reduces the predicted probability that the new household will be white by 70% for a household at the mean on all of these measures.

<<<Table 3 about here>>>

There are also aggregated effects suggesting that the race/ethnicity of the micro-neighborhood has strong effects on the likelihood that the new household is white beyond the effect of race/ethnicity of the prior household. Based on the standardized coefficients (B's), a prior African American household and the percent African American in the micro-neighborhood quite strongly reduce the likelihood that the new household will be white. Likewise, the standardized effects of a Latino household and the percent Latino in the micro-neighborhood of about -.24 are quite strong. Thus, a white household is unlikely to move into a unit occupied by an African-American or a Latino at the previous time point, and are even less likely as the percent African-American or Latino in the micro-neighborhood increases.

Crime causes racial/ethnic composition

Although these race/ethnicity effects are quite strong, we nonetheless see evidence here that the common perception of crime at the previous time point has a significantly negative effect on the likelihood that the new household will be white. A one standard deviation increase in commonly perceived crime decreases the likelihood the new household will be white .068 standard deviations, and reduces the predicted probability that the new household will be white 4.3% for a household at the mean on all other characteristics.

Recall that these are the perceptions of the residents in the micro-neighborhood at the *prior* time point, and therefore the new household's perception of crime has no effect on this measure. It is notable that this is one of the strongest non-race effects in this model: indeed, the only other micro-neighborhood characteristic that shows a significant effect is the measure of the percent living in crowded conditions, which shows a negative effect. None of the other measures—e.g., residential stability, economic resources, vacant units—have an effect. These findings imply that more commonly perceived crime in the micro-neighborhood reduces the percent white in the micro-neighborhood by reducing the likelihood that the new household will be white.

New household is African-American

I next ask whether similar factors determine the likelihood that the new residents will be African-American. There are again strong race/ethnicity effects: the strong positive effect for the presence of a black household at the previous timepoint indicates that the presence of a white or Latino household at the previous time point reduces the likelihood that the new residents will be African-American, based on equation 2 in Table 3. Thus, African-Americans are far more likely to move into a unit that was previously occupied by an African-American household. Once again, there are strong contextual effects: the standardized coefficient for percent African

American is nearly as large as that for the indicator that the previous household was African American. This implies that African-Americans are more likely to enter micro-neighborhoods that are mostly black.

<<<Table 3 about here>>>

Despite these strong race/ethnicity effects, there is again a significant effect from the common perception of crime. The common perception of crime in the micro-neighborhood at the previous time point significantly *increases* the likelihood that the new residents will be African-American, even controlling for the very strong race/ethnicity stasis effects. A one standard deviation increase in crime increases the likelihood that the new residents will be African-American .074 standard deviations, and increases the predicted probability 20%. Again, it is notable that virtually none of the other contextual measures have a significant effect on this racial/ethnic transition. It thus appears that African-Americans are more likely to enter micro-neighborhoods with higher levels of commonly perceived crime.

New household is Latino

Finally, these same processes explain the movement of a Latino household into a housing unit in equation 3 in Table 3. There are the same stasis effects for race/ethnicity, whether measured at the level of the previous household, or the level of the context of the micro-neighborhood. Despite these very strong tendencies for Latinos to move into Latino-dominated neighborhoods, there is again evidence that crime is an important factor explaining such moves. A one standard deviation increase in commonly perceived crime at the previous time point increases the likelihood that the new household will be Latino .055 standard deviations, and increases this predicted probability 15%. Once again, this is the only significant contextual effect outside of the race/ethnicity effects.

Sensitivity Analyses

Although I attempted to take into account the measurement error that is contained in the measure of commonly perceived crime, there is also the possibility of systematic bias in these reports.[14] That is, certain types of respondents and households may systematically report more or less perceived crime than would their neighbors living in the same micro-neighborhood. I assessed this by adopting an approach utilized by others (for instance, seeMorenoff, 2003) in which a fixed effects model conditioning on the micro-neighborhood of residence is first estimated.[15] From this model these coefficient estimates of the systematic bias for such individuals were obtained, and then a new measure of perceived crime was constructed purged of this bias defined as:

$y_p = y - X\mathrm{B}$

where y_p is the perception of crime purged of these biases, y is the respondent's reported perception of crime, B contains the coefficient estimates from the fixed effects models estimated, and X is a matrix containing the values for the respondent on these various characteristics. These crime perceptions purged of biases were then substituted for the original individual crime perception variable in the models.

The initial findings were robust to this new specification, as the results accounting for this systematic bias were actually somewhat stronger. In the residential mobility models, the effect of the perception of crime on white mobility was 22% stronger (.055 vs. .045 in the original models) for the individual household's perception of crime, and 30% stronger (.144 vs. .111 in the original model) for the micro-neighborhood common perception of crime (results available upon request). The results for Latinos and African Americans remained unchanged even when accounting for this systematic bias, as they showed no greater likelihood to move out of a residence in which they perceived more crime or the micro-neighborhood collectively perceived more crime. Once again, the models lacked the statistical power to detect a difference in the effect of commonly perceived crime on residential mobility between whites and these two minority groups.

The results were also consistent, and somewhat stronger, for the in-mobility models. Again, micro-neighborhoods with more commonly perceived crime reduced the likelihood that the new household would be white, and increased the likelihood that the new household would be Latino or African American (results available upon request). The size of this effect based on the unstandardized coefficients increased 23% for Latinos, 24% for African Americans, and 32% for whites. The other variables in these ancillary residential mobility and in-mobility models remained essentially unchanged.

Conclusion

Prior research has frequently found a relationship between the presence of racial/ethnic minorities in a neighborhood and the rate of crime at one point in time. Though they sometimes posit different mechanisms, these studies almost always conclude that the causal direction runs from the presence of such minorities to higher rates of crime. The present study has proposed that at least some of this relationship may be due to the fact that crime actually increases the percentage of minorities in a neighborhood. This postulate was based on the voluminous segregation literature and studies showing discriminatory behavior limiting racial/ethnic minorities' access to some neighborhoods. I utilized a unique dataset that allowed focusing on the housing unit to assess the extent to which there is disproportionate mobility in and out of high crime neighborhoods based on the race/ethnicity of residents. The findings showed that whereas white residents who perceive more nearby crime and those who live in micro-neighborhoods with more commonly perceived crime are more likely to move out of the housing unit, no such effect was detected for analogous Latino and African American residents. Furthermore, whereas white residents are less likely to move into housing units in micro-neighborhoods in which there is more commonly perceived crime, Latino and African American households are *more* likely to move into such housing units.

This study's findings suggest that the amount of crime in the micro-neighborhood may play an important role in how the racial/ethnic composition changes over time in geographic areas. A crucial implication of this finding is that prior work testing for a cross-sectional relationship between the racial/ethnic composition of a neighborhood and the crime rate and assuming that the presence of minorities increases the crime rate may have the causal explanation, at least in part, reversed. The evidence here suggests that Latinos and African-Americans are moving *into* micro-neighborhoods with more crime, explaining at least some of these cross-sectional relationships, at least based on the measure of commonly perceived crime. Furthermore, whites are more likely to leave housing units in micro-neighborhoods with higher levels of commonly perceived crime than are African Americans or Latinos.

Thus, we see evidence that the limited residential mobility options of African Americans and Latinos affect them both coming and going. Although there was modest evidence suggesting that whites may be more likely than racial/ethnic minorities to leave a housing unit in a micro-neighborhood with a greater common perception of crime, there were much stronger differences in the likelihood by race/ethnicity of entering a housing unit in micro-neighborhoods with more perceived crime. These strong in-mobility effects suggest an important avenue through which racial/ethnic transformation might occur in neighborhoods due to the presence of crime. I emphasize that these results were found for both African Americans and Latinos, mirroring recent work demonstrating that the housing options of Latinos are not much greater than those for African Americans (Iceland and Nelson, 2008).

It should also be emphasized that, other than the racial composition, commonly perceived crime was the only consistently predictive contextual factor in these models. There was no evidence that minorities are more likely to enter neighborhoods with lower economic resources or more residential instability. This highlights the important role crime appears to play in the process of racial/ethnic transformation.

The findings here complement and extend recent research suggesting that victimization may lead to residential mobility. Whereas Dugan (1999) found that being victimized increased mobility, and Xie and McDowall (2008) found that even having nearby neighbors experience a victimization led to greater out-mobility, the present study's results suggest that the common perception of crime has important effects, at least for white residents. Furthermore, the findings suggested that these common perceptions of crime were most important for the racial/ethnic transformation of neighborhoods through their effect on disproportionate in-mobility into such micro-neighborhoods by racial/ethnic minorities.

Although this study has provided important new insights for understanding the relationship between the presence of racial/ethnic minorities and crime, certain limitations should be acknowledged. First, the discussion above of the difficulty of measuring crime suggests that it would be useful for future studies to replicate these findings using alternative measures of crime rather than the common perceptions of residents. Of course, for this study's approach to be flawed implies that racial/ethnic minorities are less likely to leave neighborhoods in which residents incorrectly perceive more crime than actually exists (whereas whites are more likely to exit such neighborhoods), and they are more likely to enter neighborhoods in which residents incorrectly perceive more crime than actually exists. It is not clear what theory would predict such a process. Nonetheless, replication using other measures of neighborhood crime would enhance confidence in the findings. Second, although this study measured the contextual effects at the micro-neighborhood level, it still may be the case that a different level of geographic aggregation is appropriate. Future studies will need to test this possibility using other levels of aggregation, such as block groups or various spatial smoothing approaches. Third, although the findings are informative, it is still the case that they were limited to the period of 1985 to 1993. Future studies will need to test the extent to which racial/ethnic minorities remain constrained in their access to other neighborhoods, and the extent to which that affects their ability to either exit high crime neighborhoods, or avoid entering them. Fourth, I acknowledge that there may have been more than one household change during the four-year period between waves. Thus, it is possible that in the in-mobility models, a different type of household resided in the unit between the households observed at the two time points.[16]

An important takeaway point from this study is that racial/ethnic minorities are more likely to enter housing units located in micro-neighborhoods with more commonly perceived crime. The consequences are important for understanding how neighborhoods evolve over time. The assumption that the positive relationship between the presence of racial/ethnic minorities and crime is entirely caused by such racial/ethnic minorities clearly needs reconsideration. At least some of this relationship appears to be due to the role crime plays in changing the racial/ethnic composition of such neighborhoods. This suggests the need for future research to explicitly model the change in neighborhood crime and the change in racial/ethnic composition in a dynamic framework to tease out these effects. It appears that these constrained housing

Crime causes racial/ethnic composition

choices lead African Americans and Latinos into more dangerous neighborhoods.

Crime causes racial/ethnic composition

References:

Aldrich, Howard and Albert J. Jr Reiss. 1976. "Continuities in the Study of Ecological Succession: Changes in the Race Composition of Neighborhoods and Their Businesses." *American Journal of Sociology* 81:846-866.

Aldrich, Howard, Catherine Zimmer, and David McEvoy. 1989. "Continuities in the Study of Ecological Succession: Asian Businesses in Three English Cities." *Social Forces* 67:920-944.

Allison, Paul D. 2005. "Imputation of Categorical Variables with PROC MI." in *SUGI 30 Proceedings*. Philadelphia, PA.

Bauer, Daniel J. 2003. "Estimating multilevel linear models as structural equation models." *Journal of Educational and Behavioral Statistics* 28:135-167.

Baumer, Eric, Janet L. Lauritsen, Richard Rosenfeld, and Richard Wright. 1998. "The Influence of Crack Cocaine on Robbery, Burglary, and Homicide Rates: A Cross-City, Longitudinal Analysis." *Journal of Research in Crime and Delinquency* 35:316-340.

Boehm, Thomas P., Henry W. Herzog, Jr., and Alan M. Schlottmann. 1991. "Intra-Urban Mobility, Migration, and Tenure Choice." *The Review of Economics and Statistics* 73:59-68.

Bollen, Kenneth A. and Pamela Paxton. 1998. "Detection and Determinants of Bias in Subjective Measures." *American Sociological Review* 63:465-478.

Buck, Andrew J. and Simon Hakim. 1989. "Does Crime Affect Property Values?" *Canadian Appraiser* 33:23-27.

Bursik, Robert J. 1986. "Delinquency Rates as Sources of Ecological Change." Pp. 63-74 in *The Social Ecology*, edited by J. M. Byrne and R. J. Sampson. New York: Springer-Verlag.

Chamlin, Mitchell B. and John K. Cochran. 1997. "Social Altruism and Crime." *Criminology* 35:203-228.

Charles, Camille Zubrinsky. 2000. "Neighborhood Racial-Composition Preferences: Evidence from a Multiethnic Metropolis." *Social Problems* 47:379-407.

Chiricos, Ted, Michael Hogan, and Marc Gertz. 1997. "Racial composition of neighborhood and fear of crime." *Criminology* 35:107-131.

Chou, Chih-Ping, Peter M. Bentler, and Mary Ann Pentz. 1998. "Comparisons of Two Statistical Approaches to Study Growth Curves: The Multilevel Model and the Latent Curve Analysis." *Structural Equation Modeling* 5:247-266.

Cullen, Julie Berry and Steven D. Levitt. 1996. "Crime, Urban Flight, and the Consequences for Cities." *NBER Working Paper 5737*.

Deane, Glenn D. 1990. "Mobility and Adjustments: Paths to the Resolution of Residential Stress." *Demography* 27:65-79.

Dugan, Laura. 1999. "The Effect of Criminal Victimization on a Household's Moving Decision." *Criminology* 37:903-930.

Farley, Reynolds and William H. Frey. 1994. "Changes in the Segregation of Whites from Blacks during the 1980s: Small Steps toward a More Integrated Society." *American Sociological Review* 59:23-45.

Fischer, Claude S., Gretchen Stockmayer, Jon Stiles, and Michael Hout. 2004. "Distinguishing the Geographic Levels and Social Dimensions of US Metropolitan Segregation, 1960-2000." *Demography* 41:37-59.

Fischer, Mary J. and Douglas S. Massey. 2004. "The Ecology of Racial Discrimination." *City and Community* 3:221-241.
Frey, William H. and Reynolds Farley. 1996. "Latino, Asian, and Black Segregation in U.S. Metropolitan Areas: Are Multi-ethnic Metros Different?" *Demography* 33:35-50.
Guo, Guang and John R. Hipp. 2004. "Analysis of Linear Longitudinal Data." Pp. 347-368 in *New Handbook on Data Analysis*, edited by M. A. Hardy. London: Sage.
Hadden, Louise and Mireille Leger. 1995. *Codebook for the American Housing Survey*, vol. 1. Cambridge, MA: Abt Associates.
Hipp, John R. 2007a. "Income Inequality, Race, and Place: Does the Distribution of Race and Class within Neighborhoods affect Crime Rates?" *Criminology* 45:665-697.
—. 2007b. "Resident Perceptions of Crime: How Similar are They to Official Crime Rates?" *U.S. Census Bureau Center for Economic Studies (CES) Discussion Paper* CES-WP-07-10:36.
Hipp, John R., George E. Tita, and Robert T. Greenbaum. 2009. "Drive-bys and Trade-ups: The Impact of Crime on Residential Mobility Patterns in Los Angeles." *Social Forces* 87:1777-1812.
Iceland, John and Kyle Anne Nelson. 2008. "Hispanic Segregation in Metropolitan America: Exploring the Multiple Forms of Spatial Assimilation " *American Sociological Review* 73:741-765.
Kamata, Aki and Daniel J. Bauer. 2008. "A note on the relationship between factor analytic and item response theory models." *Structural Equation Modeling* 15:136-153.
Klaus, Patsy and Cathy Maston. 2006. *National Criminal Victimization Survey, 2005 NCJ 215244*. Washington, D.C.: Bureau of Justice Statistics.
Krivo, Lauren J. and Ruth D. Peterson. 1996. "Extremely Disadvantaged Neighborhoods and Urban Crime." *Social Forces* 75:619-648.
Krysan, Maria. 2002. "Community Undesirability in Black and White: Examining Racial Residential Preferences through Community Perceptions." *Social Problems* 49:521-543.
La Gory, Mark and John Pipkin. 1981. *Urban Social Space*. Belmont, CA: Wadsworth.
Lee, Barrett A., R. S. Oropesa, and James W. Kanan. 1994. "Neighborhood Context and Residential Mobility." *Demography* 31:249-270.
Lee, Sik-Yum and Sin-Yu Tsang. 1999. "Constrained Maximum Likelihood Estimation of Two-Level Covariance Structure Model via EM Type Algorithms." *Psychometrika* 64:435-450.
Liska, Allen E. and Paul E. Bellair. 1995. "Violent-Crime Rates and Racial Composition: Convergence Over Time." *American Journal of Sociology* 101:578-610.
Liska, Allen E., John R. Logan, and Paul E. Bellair. 1998. "Race and Violent Crime in the Suburbs." *American Sociological Review* 63:27-38.
Logan, John R., Richard D. Alba, and Shu Yin Leung. 1996. "Minority Access to White Suburbs: A Multiregional Comparison." *Social Forces* 74:851-881.
Ludtke, Oliver, Herbert W. Marsh, Alexander Robitzsch, Ulrich Trautwein, Tihomir Asparouhov, and Bengt Muthen. 2008. "The multilevel latent covariate model: A new, more reliable approach to group-level effects in contextual studies." *Psychological Methods* 13:203-229.
MacCallum, Robert C., Cheongtag Kim, William B. Malarkey, and Janice K. Kiecolt-Glaser. 1997. "Studying Multivariate Change Using Multilevel Models and Latent Curve Models." *Multivariate Behavioral Research* 32:215-253.

Massey, Douglas S. and Nancy A. Denton. 1985. "Spatial Assimilation as a Socioeconomic Outcome." *American Sociological Review* 50:94-106.
Massey, Douglas S. and Nancy A. Denton. 1987. "Trends in the Residential Segregation of Blacks, Hispanics, and Asians: 1970-1980." *American Sociological Review* 52:802-825.
—. 1993. *American Apartheid: Segregation and the Making of the Underclass*. Cambridge, MA: Harvard.
Massey, Douglas S., Andrew B. Gross, and Kumiko Shibuya. 1994. "Migration, Segregation, and the Geographic Concentration of Poverty." *American Sociological Review* 59:425-445.
Massey, Douglas S. and Zoltan L. Hajnal. 1995. "The Changing Geographic Structure of Black-White Segregation in the United States." *Social Science Quarterly* 76:527-542.
Massey, Douglas S. and Brendan P. Mullan. 1984. "Processes of Hispanic and Black Spatial Assimilation." *American Journal of Sociology* 89:836-873.
McNulty, Thomas L. 2001. "Assessing the Race-violence Relationship at the Macro Level: the Assumption of Racial Invariance and the Problem of Restricted Distributions." *Criminology* 39:467-489.
Mehta, Paras D. and Michael C. Neale. 2005. "People are Variables Too: Multilevel Structural Equations Modeling." *Psychological Methods* 10:259-284.
Mehta, Paras D. and Stephen G. West. 2000. "Putting the Individual Back Into Individual Growth Curves." *Psychological Methods* 5:23-43.
Miethe, Terance D., Michael Hughes, and David McDowall. 1991. "Social Change and Crime Rates: An Evaluation of Alternative Theoretical Approaches." *Social Forces* 70:165-185.
Morenoff, Jeffrey D. 2003. "Neighborhood Mechanisms and the Spatial Dynamics of Birth Weight." *American Journal of Sociology* 108:976-1017.
Morenoff, Jeffrey D. and Robert J. Sampson. 1997. "Violent Crime and The Spatial Dynamics of Neighborhood Transition: Chicago, 1970-1990." *Social Forces* 76:31-64.
Ouimet, Marc. 2000. "Aggregation Bias in Ecological Research: How Social Disorganization and Criminal Opportunities Shape the Spatial Distribution of Juvenile Delinquency in Montreal." *Canadian Journal of Criminology* 42:135-156.
Perkins, Douglas D., John W. Meeks, and Ralph B. Taylor. 1992. "The Physical Environment of Street Blocks and Resident Perceptions of Crime and Disorder: Implications for Theory and Measurement." *Journal of Environmental Psychology* 12:21-34.
Quillian, Lincoln and Devah Pager. 2001. "Black Neighbors, Higher Crime? The Role of Racial Stereotypes in Evaluations of Neighborhood Crime." *American Journal of Sociology* 107:717-767.
Raudenbush, Stephen W. 2001. "Toward a Coherent Framework for Comparing Trajectories of Individual Change." Pp. 35-64 in *New Methods for the Analysis of Change, Decade of Behavior: 2000-2010*, edited by L. M. Collins and A. G. Sayer. Washington, D.C.: American Psychological Association.
Roncek, Dennis W. 1981. "Dangerous Places: Crime and Residential Environment." *Social Forces* 60:74-96.
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.
Rosenbaum, Emily. 1994. "The Constraints on Minority Housing Choices, New York City 1978-1987." *Social Forces* 72:725-747.

Rosenbaum, Emily and Grigoris Argeros. 2005. "Holding the Line: Housing Turnover and the Persistence of Racial/Ethnic Segregation in New York City." *Journal of Urban Affairs* 27:261-281.
Rountree, Pamela Wilcox. 1998. "A Reexamination of the Crime-Fear Linkage." *Journal of Research in Crime and Delinquency* 35:341-372.
Rubin, Donald B. 1987. *Multiple Imputation for Nonresponse in Surveys*. New York: Wiley.
Sampson, Robert J. 1987. "Urban Black Violence: The Effect of Male Joblessness and Family Disruption." *American Journal of Sociology* 93:348-382.
—. 2009. "Disparity and Diversity in the Contemporary City: Social (Dis)order Revisited." *British Journal of Sociology* 60:1-31.
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. and Stephen W. Raudenbush. 1999. "Systematic Social Observation of Public Spaces: A New Look at Disorder in Urban Neighborhoods." *American Journal of Sociology* 105:603-651.
—. 2004. "Seeing Disorder: Neighborhood Stigma and the Social Construction of "Broken Windows"." *Social Psychology Quarterly* 67:319-342.
Sampson, Robert J., Stephen W. Raudenbush, and Felton Earls. 1997. "Neighborhoods and Violent Crime: A Multilevel Study of Collective Efficacy." *Science* 277:918-924.
Sampson, Robert J. and William Julius Wilson. 1995. "Toward a Theory of Race, Crime, and Urban Inequality." Pp. 37-54 in *Crime and Inequality*, edited by J. Hagan and R. D. Peterson. Stanford, CA: Stanford University Press.
Sampson, Robert J. and John D. Wooldredge. 1986. "Evidence that High Crime Rates Encourage Migration away from Central Cities." *Sociology and Social Research* 70:310-314.
Schafer, Joseph L. 1997. *Analysis of Incomplete Multivariate Data*. New York: Chapman and Hall.
Schuerman, Leo and Solomon Kobrin. 1986. "Community Careers in Crime." *Crime and Justice* 8:67-100.
Schwartz, Amy Ellen, Scott Susin, and Ioan Voicu. 2003. "Has Falling Crime Driven New York City's Real Estate Boom?" *Journal of Housing Research* 14:1-35.
Shaw, Clifford and Henry D. McKay. 1942. *Juvenile Delinquency and Urban Areas*. Chicago: University of Chicago Press.
Skogan, Wesley G. 1990. *Disorder and Decline: Crime and the Spiral of Decay in American Neighborhoods*. New York: Free Press.
South, Scott J. and Kyle D. Crowder. 1997a. "Escaping Distressed Neighborhoods: Individual, Community, and Metropolitan Influences." *American Journal of Sociology* 102:1040-1084.
—. 1997b. "Residential Mobility Between Cities and Suburbs: Race, Suburbanization, and Back-to-the-City Moves." *Demography* 34:525-538.
South, Scott J. and Steven F. Messner. 2000. "Crime and Demography: Multiple Linkages, Reciprocal Relations." *Annual Review of Sociology* 26:83-106.
Speizer, Ilene S. and Kenneth A. Bollen. 2000. "How Well do Perceptions of Family Planning Service Quality Correspond to Objective Measures? Evidence from Tanzania." *Studies in Family Planning* 31:163-177.
Taylor, Ralph B. 1995. "The Impact of Crime on Communities." *The Annals of the American Academy of Political and Social Science* 539:28-45.

—. 2001. *Breaking Away from Broken Windows: Baltimore Neighborhoods and the Nationwide Fight Against Crime, Grime, Fear, and Decline*. Boulder, CO: Westview.
Taylor, Ralph B., Stephen D. Gottfredson, and Sidney Brower. 1984. "Block Crime and Fear: Defensible Space, Local Social Ties, and Territorial Functioning." *Journal of Research in Crime and Delinquency* 21:303-331.
Thaler, Richard. 1978. "A Note on the Value of Crime Control: Evidence from the Property Market." *Journal of Urban Economics* 5:137-145.
Tita, George E., Tricia L. Petras, and Robert T. Greenbaum. 2006. "Crime and Residential Choice: A Neighborhood Level Analysis of the Impact of Crime on Housing Prices." *Journal of Quantitative Criminology* 22:299-317.
Turner, Margery A., Stephen Ross, George C. Galster, and John Yinger. 2000. "Discrimination in metropolitan housing markets: National results from Phase I HDS 2000." U.S. Department of Housing and Urban Development, Washington, D.C.
Van Valey, Thomas L., Wade Clark Roof, and Jerome E. Wilcox. 1977. "Trends in Residential Segregation: 1960-1970." *American Journal of Sociology* 82:826-844.
Warner, Barbara D. and Pamela Wilcox Rountree. 1997. "Local Social Ties in a Community and Crime Model: Questioning the Systemic Nature of Informal Social Control." *Social Problems* 44:520-536.
Wilson, William J. 1987. *The Truly Disadvantaged: The Inner City, the Underclass, and Public Policy*. Chicago: University of Chicago Press.
Wolfgang, Marvin E. and Franco Ferracuti. 1967. *The subculture of violence: Towards an integrated theory in criminology*. London: Tavistock.
Xie, Min and David McDowall. 2008. "Escaping Crime: The Effects of Direct and Indirect Victimization on Moving." *Criminology* 46:809-840.

Endnotes

[1] Another possible explanation is information asymmetry. That is, current residents of the neighborhood likely have a better sense of how the rate of crime in a neighborhood is changing compared to potential new residents. In such an instance, a household may be willing to move into the neighborhood simply because they are unaware that the level of crime is higher than they expected. There is some evidence in support of this: households who have lived longer in the neighborhood perceive more crime (Sampson, Raudenbush, and Earls, 1997) and more risk of crime (Taylor, Gottfredson, and Brower, 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). This possibility has little effect on the posited model here, except that it introduces a stochastic element into the in-mobility decisions of households. As a consequence, it may slow the racial/ethnic transition of a neighborhood, but not reverse or stop it. Most likely this would be manifested in a greater likelihood of white residents abandoning a neighborhood, but no difference in their likelihood of entering the neighborhood (assuming complete asymmetry in information regarding neighborhood crime). The models below are able to assess the extent to which this is actually the case.
[2] In the American Housing Survey, sample units were selected from the 1980 Census Sample Housing Unit Record File. A Housing Unit Coverage Study was performed to locate units

missed by the 1980 census, and an additional sample was selected from the units located by this study (such as non-residential to residential units, new mobile home parks, etc). Building permits are also sampled to represent newly constructed housing since the 1980 census, and was the source of the new micro-neighborhoods added in the 1989 and 1993 waves. To construct the frame for building permits: clusters of four new construction units were formed using information from sample building permit offices; one construction unit was subsampled from each cluster. They used the 1980 characteristics of the units in these ED's as stratifiers based on: 1) geographic location (central city, urbanized area outside of central city, urban outside of urbanized area, rural); 2) tenure; 3) number of rooms; 4) value of unit or gross rent (For a more complete description of the AHS sampling design, see Aldrich and Reiss, 1976; Hadden and Leger, 1995).

[3] The number of households in these micro-neighborhoods can vary. Over these three waves, just 0.7% of the micro-neighborhoods have between 5 and 7 households, 5.1% have between 8 and 10, 78.5% have 11, 8.2% have 12, 4.2% have 13, 0.8% have 14, 2.1% have between 15 and 19, and 0.4% have 20 or 21.

[4] I can assess the degree to which mobility varies across residents within the same micro-neighborhood compared to across micro-neighborhoods. I find that about 25% of the variance occurs across micro-neighborhoods, whereas the other 75% occurs within. This suggests a fair amount of clustering of movers within micro-neighborhoods.

[5] There was no evidence that including this individual-level measure along with the micro-neighborhood level measure of common perception of crime caused estimation difficulties. The correlation between the two measures was .55, which is not excessively high. Furthermore, estimating a model without this individual-level measure showed a similar effect for the common perception of crime measure (with a slightly larger coefficient), and a relatively similar standard error. Thus, there is little evidence that including this individual-level measure introduces multicollinearity problems.

[6] The average R-square for the household-level perceived crime measures is .23, suggesting that about 23 percent of these responses are accounted for by this neighborhood-level measure of commonly perceived crime, whereas the other 77 percent is measurement error. This emphasizes the importance of explicitly taking into account this measurement error. The latent measure has a reliability of .75, which is explicitly taken into account in the estimation strategy.

[7] There is a large literature showing that hierarchical linear models (HLM) and structural equation models (SEM) will provide identical results for several types of models. Numerous studies have shown that HLM and SEM will yield identical estimates for trajectory models (Chou, Bentler, and Pentz, 1998; Guo and Hipp, 2004; MacCallum, Kim, Malarkey, and Kiecolt-Glaser, 1997; Mehta and West, 2000; Raudenbush, 2001). Recent work has shown the two techniques will yield identical results even when the data are unbalanced over level two units (Bauer, 2003; Lee and Tsang, 1999). Two nice didactic papers showing how HLM and SEM can be used to obtain identical results are Bauer (Bauer, 2003) and Mehta and Neale (Mehta and Neale, 2005). It is also important to point out that whereas some scholars might assume that using an item response theory (IRT) approach to create scales would be preferable to the SEM approach, in fact a paper shows the exact mathematical relationship between SEM and IRT model parameters (Kamata and Bauer, 2008).

[8] This selection model included the measures for the residential mobility model shown in Table 2. Given that these household-level characteristics predict residential mobility (the selection

process) but have little effect on the type of households that move into the neighborhood, the level of multicollinearity is reduced in the final model relative to other implementations of such a selection model. I nonetheless performed sensitivity analyses by estimating the models without the inverse Mills ratio. The results were extremely similar to those in the models presented. Thus, the results are essentially the same whether or not selection effects are taken into account.

[9] I used the Proc MI procedure in SAS to perform the imputations. Only information from the current wave was included when imputing values (given that the household in other waves could be a different one). The imputation model included all variables contained in the substantive models, as well as several other possibly important measures to get more precise estimates of the missing values. All imputed values were constrained to fall within the range of values in the original measure, and values were not rounded to integers given Monte Carlo simulation evidence that such an approach has poor properties (Allison, 2005).

[10] There were only modest amounts of missing data. For example, among housing units that responded to the survey, there was less than 1% missing data for any of the variables. For the neighborhood common perception of crime measure, there was 6.2% missing data for the indicators of this latent variable (as missing data for this measure occurs in instances in which a household does not respond to the survey, or the housing unit was empty). See the technical appendix for an explanation of the data structure.

[11] Given that these models are estimated within the SEM framework rather than HLM, the overall fit of the model can be assessed. However, given that I am estimating parallel logit models, overidentification in the model only occurs due to the latent variable for the micro-neighborhood common perception of crime. I therefore assessed the fit of the confirmatory factor analysis (CFA) of the common perception of crime, and found an excellent fit for the overall sample: an RMSEA of .018, and values of .99 for the Tucker Lewis Index (TLI) and the Comparative Fit Index (CFI) (values less than .05 for the RMSEA, and greater than .90 for the other measures are generally considered an indicator of a very good fit). These values remained very good when estimating the CFA separately by race/ethnicity: for instance, the RMSEA values were .051 for Latinos, .041 for African Americans, and .021 for whites. The model fits were similar for the residential out-mobility models; furthermore, the in-mobility model with the combined sample also showed an excellent fit with an RMSEA of .017, and CFI and TLI values of .97.

[12] This is computed by setting the other variables in the model to their mean value, and then setting the variable of interest to specific values and computing the predicted probability of moving for these values (using the standard normal cumulative distribution since these outcomes are estimated as a probit model). I then compute the percentage change between these two values.

[13] This is assessed by estimating additional models constraining the parameter for the effect of the common perception of crime to be equal over these groups, and assessing the change in the overall fit of the model as a chi square test.

[14] There is also the possibility of measurement error in these individual assessments of perceived crime. Indeed, as noted above in footnote 5, about 77% of these reports are measurement error. I tested for and found that the degree of measurement error differed by race/ethnicity, as it tended to be somewhat lower for whites compared to the Latinos and African Americans. I estimated additional models taking into account this measurement error (by creating a latent variable of individual perceived crime with this single indicator and an error variance constrained to a specific value that achieves appropriate reliability), and unsurprisingly the

perception of crime for a household did not affect mobility for any of these groups. The effect of the common perception of crime on the mobility of whites remained robust in these models. If we assume that the perception is of theoretical interest, regardless of the degree of "error" it contains, then this study's modeling approach (and that of virtually all prior studies) ignoring this measurement error is appropriate.

[15] I included the following individual- and household-level measures in the equation: female, age, black, Latino, other race, years of education, household income, length of residence (logged), an indicator of whether it is the first year in the residence, ownership status, currently married, currently divorced, currently widowed, the presence of children less than 5 years of age, the presence of children 6 to 12 years of age, the presence of children 13 to 18 years of age.

[16] Of course, if the intervening household was of the same race/ethnicity as the new household observed, the results would be unchanged. It is only if the intervening household(s) is of a different race/ethnicity that results could change: of course, the fact that the intervening household did not stay long in the household suggests that missing them may not be a serious limitation to the design. The present study would also miss a household that moved out and then moved back in. Such temporary moves are of less theoretical interest, as they do not change the composition of the neighborhood.

Tables and Figures

Table 1. Summary statistics of variables used in analyses

	Mean	Std. Dev.
Racial composition		
White. 1985	0.774	0.418
White. 1989	0.740	0.439
White, 1993	0.720	0.449
African-American, 1985	0.129	0.335
African-American, 1989	0.135	0.342
African-American, 1993	0.147	0.354
Latino, 1985	0.072	0.259
Latino, 1989	0.084	0.277
Latino, 1993	0.095	0.293
Characteristics of household		
Moved	0.441	0.497
Length of residence (logged)	1.842	1.162
Owner	0.572	0.482
Persons per room	0.492	0.294
Education	12.736	3.144
Household income (logged)	3.076	2.757
Have children less than 6 years of age	0.207	0.517
Have children 6 to 12 years of age	0.230	0.556
Have children 13 to 18 years of age	0.198	0.500
Age	48.431	17.347
Divorced	0.177	0.382
Single	0.160	0.367
Widowed	0.139	0.346
Perceived crime, total sample	0.548	0.928
Perceived crime, African Americans	0.840	1.089
Perceived crime, whites	0.524	0.910
Perceived crime, Latinos	0.674	1.034
Characteristics of micro-neighborhood		
Common perception of neighborhood crime	0.548	0.481
Proportion new households	0.465	0.247
Proportion owners	0.572	0.354
Proportion vacant units	0.071	0.144
Proportion in crowded conditions	0.035	0.085
Average household income (logged)	3.076	1.704
Proportion African-American	0.131	0.269
Proportion white	0.748	0.319
Proportion Latino	0.077	0.169
Proportion other race	0.026	0.067
Proportion with children	0.584	0.505

N = 14,794 household years

Table 2. Predicting the residential mobility of the previous residents in the unit, American Housing Survey special neighborhood sub-sample, 1985-89, 1989-93

	(1)		(2)		(3)	
	White sample		African American sample		Latino sample	
	Household	Micro-neighborhood	Household	Micro-neighborhood	Household	Micro-neighborhood
Perception of crime	0.045 **	0.111 *	0.021	0.029	-0.016	0.044
	(0.017)	(0.046)	(0.040)	(0.115)	(0.046)	(0.132)
Length of residence (logged)	-0.367 **		-0.340 **		-0.395 **	
	(0.018)		(0.043)		(0.057)	
Percent new households		0.644 **		0.676 **		0.971 **
		(0.097)		(0.218)		(0.261)
Home owner	-0.611 **	0.184 *	-0.637 **	0.196	-0.543 **	0.282
	(0.049)	(0.081)	(0.113)	(0.191)	(0.144)	(0.237)
Percent vacant units		0.066		0.284		0.892 *
		(0.171)		(0.490)		(0.437)
Person per room	0.129		0.221		-0.198	
	(0.090)		(0.189)		(0.140)	
Percent in crowded conditions		0.257		-0.161		0.390
		(0.354)		(0.575)		(0.408)
Years of education	0.005		-0.014		-0.021	
	(0.006)		(0.015)		(0.015)	
Household income	0.003	-0.012	-0.022	-0.064	0.020	-0.051
	(0.008)	(0.013)	(0.026)	(0.050)	(0.027)	(0.055)
Percent African American		0.066		-0.131		-0.092
		(0.138)		(0.168)		(0.384)
Percent Latino		0.053		0.061		-0.132
		(0.190)		(0.347)		(0.232)
Percent other race		-0.348		-1.084		0.006
		(0.311)		(0.911)		(0.798)

Crime causes racial/ethnic composition

Have children less than 6 years of age	0.172 **		0.195 *		0.082	
	(0.034)		(0.083)		(0.081)	
Have children 6 to 12 years of age	-0.015		0.097		0.057	
	(0.031)		(0.071)		(0.062)	
Have children 13 to 18 years of age	-0.006		-0.063		-0.008	
	(0.039)		(0.072)		(0.067)	
Percent with children		0.033		-0.116		0.001
		(0.037)		(0.096)		(0.101)
Age	-0.002 *		-0.003		-0.004	
	(0.001)		(0.003)		(0.004)	
Divorced	0.274 **		0.216 †		0.158	
	(0.047)		(0.114)		(0.120)	
Single	0.166 **		0.097		0.051	
	(0.060)		(0.110)		(0.135)	
Widowed	0.371 **		0.123		-0.043	
	(0.062)		(0.146)		(0.212)	
Year	-0.072 *		0.122		-0.142	
	(0.030)		(0.092)		(0.094)	
Variance explained	0.411		0.385		0.357	
N	11,590		2,032		1,172	

*** p < .01(two-tail test), * p < .05 (two-tail test), † p < .05 (one-tail test). Standard errors in parentheses. Structural equation models.*

Table 3. Predicting the race/ethnicity of the new household occupants, American Housing Survey special neighborhood sub-sample, 1985-89, 1989-93

	(1)				(2)				(3)			
	New occupants are white				New occupants are African American				New occupants are Latino			
	Household		Micro-neighborhood		Household		Micro-neighborhood		Household		Micro-neighborhood	
	b	B	b	B	b	B	b	B	b	B	b	B
Common perception of crime			-0.212	-0.068 **			0.223	0.073 **			0.159	0.059 *
			(0.066)				(0.079)				(0.067)	
African-American	-1.477	-0.335 **	-1.753	-0.308 **	1.688	0.386 **	2.165	0.383 **	-0.065	-0.017	-0.183	-0.037
	(0.088)		(0.155)		(0.093)		(0.148)		(0.118)		(0.196)	
Latino	-1.211	-0.236 **	-1.997	-0.241 **	0.016	0.003	-0.222	-0.027	1.422	0.320 **	2.403	0.334 **
	(0.079)		(0.199)		(0.141)		(0.272)		(0.079)		(0.220)	
Other race	-0.378	-0.019	-3.723	-0.168 **	0.138	0.007	1.132	0.052 *	0.514	0.030	0.491	0.025
	(0.251)		(0.493)		(0.353)		(0.466)		(0.391)		(0.523)	
Length of residence (logged)	-0.117	-0.088 **			0.131	0.100 *			0.135	0.117 *		
	(0.044)				(0.058)				(0.055)			
Percent new households			-0.016	-0.003			0.212	0.035			0.179	0.034
			(0.137)				(0.188)				(0.181)	

Crime causes racial/ethnic composition

Percent home owners			0.086	0.021			-0.079	-0.019			0.140	0.039
			(0.110)				(0.165)				(0.146)	
Percent vacant units			0.235	0.021			-0.109	-0.010			-0.141	-0.015
			(0.206)				(0.230)				(0.237)	
Percent in crowded conditions			-0.937	-0.061 *			-0.391	-0.026			0.425	0.032
			(0.374)				(0.508)				(0.421)	
Average household income			-0.002	-0.002			-0.023	-0.025			-0.038	-0.047
			(0.023)				(0.037)				(0.030)	
Percent with children			0.006	0.002			0.004	0.001			0.015	0.006
			(0.053)				(0.075)				(0.070)	
Year			0.104	0.035			0.021	0.007			-0.031	-0.012
			(0.068)				(0.073)				(0.065)	
Inverse Mills ratio	0.301	0.084 *			-0.229	-0.065			-0.410	-0.132 *		
	(0.151)				(0.201)				(0.172)			
R-square	0.55				0.54				0.29			
N	6,865				6,865				6,865			

*** p < .01(two-tail test), * p < .05 (two-tail test), † p < .05 (one-tail test). Standard errors in parentheses. Structural equation models.*

Technical Appendix

I describe here how the data were structured and the models estimated. The data originally are in "long" format: each row in the data represents an individual household. Multiple households are from each of the micro-neighborhoods in each of the years. Rather than creating a level two measure of the average perception of crime of the residents in the micro-neighborhood, I wished to account for the measurement error contained in these individual responses (for a detailed description of this approach, see Ludtke et al., 2008).

To account for this individual-level measurement error, one SEM approach swings the data "wide". After doing so, the data is structured such that each row in the dataset contains information for a particular micro-neighborhood. The "variables" in this newly structured dataset now represent the response of a particular person in the micro-neighborhood for the particular construct. Thus, if there are 11 households in each micro-neighborhood, then there will be a crime1 variable that measures the perception of crime in the neighborhood by person "1", a crime2 variable that measures the perception of crime in the neighborhood by person "2", on up to a crime11 variable that measures the perception of crime in the neighborhood by person "11". These 11 variables can then be treated as indicators of a latent variable of the common perception of crime in the neighborhood: thus, this is a CFA with 11 indicators in which each indicator represents the response of a particular household (rather than the response of a person regarding a particular variable, as is more common in factor analysis). Because each row represents a micro-neighborhood, the clustering is accounted for.

However, a limitation to swinging the data wide is that it can create a large amount of missing data if the number of persons living in each micro-neighborhood fluctuates considerably. If every micro-neighborhood had eleven households, there would be no problems: there would now be eleven instantiations of every variable from the “long” dataset. Although this can be cumbersome given the large number of variables, estimating the model is nonetheless straightforward. However, if the number of persons in each micro-neighborhood has a wider range (say, from 5 up to 20), then the decision is more challenging. One option would be to choose the minimum number of persons in each neighborhood: this would result in a new wide dataset in which each micro-neighborhood would be represented by 5 persons. This has the advantage of minimizing missing data. However, it has the severe disadvantage of discarding a considerable amount of information as it would only randomly select 5 persons from each micro-neighborhood, and then discard the information on all the other persons in the neighborhoods. At the other extreme, the researcher could choose to keep the maximum number of persons in a micro-neighborhood. In this case, there would be 20 new variables created for each previous variable in the “long” dataset. The advantage of this is that no information is discarded. However, a disadvantage is that it introduces a considerable amount of missing data which can cause estimation problems. Note that this missing data does not cause bias, as it is missing completely at random (for example, no “20th” person was surveyed for a particular micro-neighborhood). If the proportion of missing data is high enough, the model will simply fail to converge. A middle ground approach is to choose the number of persons per neighborhood based on the modal or median number of persons in micro-neighborhoods. For example, in the AHS the median and modal value is 11 households in a micro-neighborhood. This approach loses some information (based on the number of micro-neighborhoods with more than 11 households), and will create some missing data (based on the number of micro-neighborhoods with less than 11 households). However, this amount of missing data did not provide estimation difficulties for these data, given that only 2% of the micro-neighborhoods had fewer than 11 households.

Although swinging the data wide and then constraining the analysis to 11 households per neighborhood has the undesirable characteristic of losing some information, this is a minor issue when estimating the common perception of crime in the neighborhood as estimates would only be somewhat more precise when using all persons in a neighborhood rather than with 11 households. Furthermore, in these data fully 79.9% of the micro-neighborhoods had exactly 11 households, 16.4% had between 12 and 15 households, and just 1.9% percent had more than 15 households, suggesting minimal loss of precision. Of more concern would be the loss of information regarding the mobility behavior of these additional persons. I therefore adopted a hybrid approach: for the perception of crime measure, I swung wide a dataset containing just this measure for 11 randomly selected households in each micro-neighborhood, and then re-merged this small dataset back with the initial, long dataset. The result is a dataset that is “long” for all of the variables, but then has these 11 indicators for the common perception of crime in the neighborhood.

The model estimated then uses a dataset in which each row is a household, but the common perception of crime indicators are arrayed wide. Therefore, it is necessary to account for the clustering in these data for any of the micro-neighborhood level variables (including the common perception of crime). This is done by correcting the standard errors with robust standard errors computed by Mplus 4.1, which explicitly account for the clustering that occurs within micro-neighborhood within year.

This latent variable of the common perception of crime in the micro-neighborhood explicitly accounts for measurement error, and does not simply sum up the responses (Ludtke et al., 2008). These factor loadings, intercepts, and error terms are constrained equal, which is reasonable given that persons are randomly ordered within each micro-neighborhood. There is therefore no reason to suppose that, for example, person "3" on average will be less accurate reporting perceived crime than person "7" on average. This mirrors the approach taken in the multilevel literature when estimating within the "ecometric" framework (Sampson and Raudenbush, 1999).

Note that this approach allows estimating a multiple groups model by race/ethnicity. Recent SEM software developments have made possible an approach of directly estimating the random variance of a level 1 variable (such as perceived crime) with a "long" dataset. The problem with this approach for the present study's question is that in a multiple groups analysis, only the Latino respondents in a micro-neighborhood would contribute to the estimate of commonly perceived crime in the Latino model; likewise, only the African American residents would contribute to the estimate in the African American model. This makes little sense, as a more appropriate estimate takes into account the perceptions of *all* residents in the micro-neighborhood. The present study's hybrid approach allows utilizing all residents' responses when creating this measure.

Another issue is a current software limitation: when estimating a multiple groups analysis, Mplus currently can only estimate this level 2 random term when using this approach if the variable is specified as endogenous (that is, it is an outcome in the model). This does not map onto the theoretical model given that this common perception of crime was specified as exogenous, Furthermore, the current Mplus software implementation cannot estimate this model using a maximum likelihood estimator (using a numerical integration approach), but instead estimates it as a weighted least squares estimator (which mirrors this study's models, so little would be gained by such an approach).