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Living with Crime: The Implications of Racial/ Ethnic Differences in Suburban Location*

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Abstract

In this article, we investigate racial/ethnic differences in exposure to crime in suburbs In our research site, part of the greater New York metropolitan region, we find clear-cut racial/ethnic differences in average exposure to property and violent crime: blacks are most exposed, whites and Asians are least; Hispanics are in between. Then, using a novel technique for constructing cross-level regression models when a matching data set is not available, we test in two stages whether (1) individual-level and (2) contextual variables can explain differences among the groups. Such individual-level variables as household income and homeownership do predict the crime level of an individual's community of residence, but they do little to explain group differences in exposure to crime, especially between blacks and other groups. Three contextual variables, reflecting community racial composition, extent of poverty, and population size, constitute a more powerful explanation of individual and group variations.

In recent decades, suburban crime has risen faster than that in cities. During the 1970s, for example, the violent crime rate in suburbs increased by more than 100%, while that in large cities grew by 44% (Logan & Messner 1987). But crime is not spread uniformly throughout suburbia (Gottdiener 1982; Stahura, Huff & Smith 1980): some suburbs have retained a reputation as safe communities, while others have come to resemble cities in this respect. Thus, crime is contributing to the differentiation among suburbs and is adding to what Logan (1978) calls the "hierarchy of place" — the structured inequalities among communities that enhance the quality of life and life chances of residents of the most desirable places while detracting from those of residents of less desirable areas.

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The growth and concentration of suburban crime potentially intersect with another major social trend, the suburbanization of minorities (Alba & Logan 1991; Massey & Denton 1988). The minority populations in the suburban portions of American metropolitan areas are increasing at a more rapid rate than are populations of non-Hispanic whites. The increases are due to the suburbanization of older minorities, notably black Americans, as well as of recent immigrants, some of whom appear to be bypassing the stage of settlement in inner-city enclaves (Alba & Logan 1991; Frey & Speare 1988; Waldinger 1989). But minorities are not distributed at random among suburbs, even though their segregation is demonstrably lower there than in central cities (Massey & Denton 1988). The strongest body of evidence has been developed for suburban blacks, and it shows that blacks in suburbia tend to be concentrated in communities that are near to central-city ghettoes, have smaller per capita tax bases and provide fewer services, and are disadvantaged in other tangible respects (Logan & Alba 1993; Logan & Schneider 1984; Schneider & Logan 1982; Schneider & Phelan 1993). Less is known about the characteristics of the suburbs in which other minorities settle.

The crime rate is self-evidently an aspect of quality of life that marks some communities as preferable to others. As Sampson (1985) reports, the majority of personal crimes "occur near the residences of both victim and offender" (see also Pyle et al. 1974). Thus, residence in a high-crime suburb increases the risk of victimization, which we will refer to as "exposure" to crime. No doubt, in forsaking cities for suburbs, many minority households, like majority households, are seeking communities where this exposure is lower. But are they able to achieve this goal to the same degree as their non-Hispanic white peers? At one level, this question can be answered through ecological studies of crime: what is the relationship between a community's racial composition and its crime rate? If the suburbs in which many African Americans reside are more ghetto-like than the average suburb, it is reasonable to hypothesize that members of the group are more exposed to crime than their white counterparts. A somewhat different chain of reasoning leads to a similar hypothesis for other minorities. If Asians and Hispanics enter suburban communities where recent immigrants are more numerous, then the social disorganization associated with high in-migration rates may lead to higher crime rates. Both of these suppositions can be supported by findings from the criminological literature concerning the ecological correlates of high-crime areas. In this literature, the crime rate of a community is understood to be a consequence of its population composition. For example, the crime rate may be high because a large proportion of residents are nonwhite or because of other population characteristics associated with racial composition (Blau & Blau 1982; Messner 1983; Sampson & Groves 1989).

Another interpretation of such ecological correlations is that the crime rate also plays a causal role in locational patterns (Liska & Bellair 1993). For example, there is some evidence that migration from central cities to suburbs is affected by central-city crime as a "push" factor (Frey 1979). Hence, locational choices may be affected by perceptions of community quality, including exposure to crime. This is an interpretation that we explore in this article.

Our approach also departs from previous ecological studies in another way. Reciprocal causation could be studied by analysis of crime rates and aggregate population characteristics in a time-series model. Instead, we model the process mainly at the level of individuals. A characteristic of the place where a person lives — like a low exposure to crime — can be viewed as an attainment, a resource to which one gains access in proportion to one's personal resources and preferences. Following the same logic as a traditional status attainment model, these predictors may include one's income and education, immigration status, or ability to purchase rather than rent a home. We assume that all people prefer to live in communities with lower crime rates and that people with greater personal resources are more capable of doing so. This establishes a baseline for questions about racial differences that can *only* be addressed by causal models at the individual level. Do blacks live in suburbs with higher crime rates because they are poorer or less educated than whites? Do Asians and Hispanics live in higher-crime suburbs because they are more likely to be recent immigrants or non-English speakers? Or are there segregating processes through which non-Hispanic whites, blacks, Asians, and Hispanics of similar social background are located in different kinds of places? We have previously found that blacks (and to a lesser extent, Hispanics, but not Asians) live in suburbs with lower proportions of white residents and lower average income levels than would be predicted from their own socioeconomic standing, family status, or nativity (Alba & Logan 1993; Logan & Alba 1993). In this article, we apply a similar methodology to exposure to crime, which is a more tangible indicator of the quality of life in a community. Thus, we pursue somewhat different questions than those that have motivated past research on places and the risk of crime: our interest lies neither in the characteristics that determine who is likely to be a crime victim (cf. Smith & Jarjoura 1989), nor in those that concentrate crime in some places rather than others. We take for granted that there are differences among suburbs in rates of crime and that these correlate with such ecological variables as the percentages of residents who are black and/or poor (e.g., Roncek 1981; Sampson 1987; Stahura, Huff & Smith 1980). Rather, we are concerned with the processes that spatially distribute individuals and whether these lead to unequal residential outcomes, including exposure to crime.

We employ a new method of analyzing locational processes at the individual level, a method which allows us to investigate the determinants of residence in suburbs with greater or lesser crime rates. We do this specifically for suburbs in the New Jersey portion of the greater New York City metropolitan area.[1] We first estimate a single equation in which members of all four major racial/ethnic groups are pooled together. The effects of dummy variables representing the groups offer an initial estimate of net racial differences in exposure to crime, controlling for other individual characteristics. We then estimate separate equations for the four groups, which reveal similarities and differences among groups in the background characteristics (such as income and education) that are associated with living in suburbs having lower or higher crime rates.

As a final and logically necessary step, we introduce contextual variables into these equations — that is, community-level variables that are known to be associated with the level of crime. This procedure allows us to pinpoint what aspects of the residential sorting process — the steering of minorities to suburbs with low proportions of white residents, or with high poverty rates, or high housing density — account for the disparities revealed in the preceding analysis. It also provides some additional evidence regarding the direction of causality. We argue that the possible effect of race on crime rates is reflected in these final models by inclusion of the racial composition of the community as an ecological variable. Thus, if members of a minority group are found to live in communities with higher crime rates even after controlling for individual-level characteristics and for the communities' racial composition, we interpret this result as evidence that the crime rate has affected residential processes.

Theory and Method

Our theoretical starting point lies in two models of locational processes. The first is the model of spatial assimilation, which views the spatial distribution of groups as a reflection of the state of their socioeconomic attainment and assimilation (Massey 1985). Descended from the ecological tradition, the model envisions the locations of individuals and families as largely the outcome of a market-driven process and hence of individual-level characteristics. For members of minority groups in particular, it predicts that, as they acculturate and establish themselves in American labor markets, they convert socioeconomic and assimilation progress into residential gain by purchasing residence in places with greater advantages and amenities, lower crime among them (Massey, Condran & Denton 1987).

This model should apply with special force to suburbs, since most ethnic enclaves are located in central cities and since location in suburbia is known to be related to assimilation variables and to a decline in segregation from the majority (Alba & Logan 1991; Massey & Denton 1987, 1988). The model implies that, within suburbia, the locational process and, in particular, the quality of life available in community of residence should be described well by individual-level variables, such as income, education, and English-language ability. Implied also is that these relationships should function in similar ways for different racial/ethnic groups. However, scholars employing this framework do acknowledge the African-American case as an exception to the predicted pattern (e.g., Massey & Denton 1988).

The model of place stratification modifies in important respects the predictions to be derived from spatial assimilation. According to the model, communities are hierarchically ranked: they are associated with more or less favorable life chances and qualities of life for the people who reside in them (Logan 1978; Logan & Molotch 1987). This hierarchy is seen additionally as a means by which more-advantaged groups, e.g., affluent non-Hispanic whites, seek to preserve social distance from less-advantaged ones. That is, the hierarchy of place coincides to an important degree with the mapping of racial and ethnic groups across space. Expressed on another plane, communities, which are engaged in a struggle with each other to preserve or enhance their hierarchical position, employ a variety of strategies, such as restrictive zoning, to exclude less-favored groups. Private acts of discrimination may have the same effect. As a result, minorities find it difficult to enter some communities and frequently must pay more for housing in order to do so (see Farley & Allen 1987; Logan & Stearns 1981; Rieder 1985; Shlay & Rossi 1981).

The place stratification model indicates that group membership is fundamental to any analysis of locational processes. Those minority groups most vulnerable to discrimination, e.g., blacks and some Hispanics, are limited in their ability to reside in the same communities as comparable whites. Thus, the members of these groups may not be fully able to convert socioeconomic and assimilation gains into residence in the same communities as the majority. This reasoning implies that the "returns" on individual achievements, such as income and English-language ability, may differ substantially across groups. In effect, it "costs" members of some groups more to achieve desirable locational outcomes, if they are able to achieve them at all.

In applying these theoretical models to the analysis of crime, we view a low crime rate as a desirable feature of a community, one of the characteristics that serves to rank it in a hierarchy of places. At the same time, individuals attempt to locate themselves favorably in terms of this hierarchy and are able to achieve this insofar as their own characteristics, including racial/ethnic membership, allow. This reasoning leads to a unified analytical model that represents how individuals are mapped into communities of greater or lesser crime rates, expressed in the following way:

$$Y_j = a + b_1X_{1ij} + b_2X_{2ij} + b_3X_{3ij} + \epsilon_{ij}$$

where Y_j is a community-level measure of crime, X_{1ij} is the household income (or another human-capital variable) for individual or household i in community j, X_{2ij} is English-language ability (or another assimilation measure), and X_{3ij} represents other (possibly control) variables, such as household configuration or age. The model is estimated for the individual or the household as the unit.

This model can be estimated for the entire population of a region, in which case it will contain race/ethnicity as an additional variable, or separately by racial/ ethnic group. We will estimate the model in both ways in this article, but the latter type addresses more directly the hypotheses that motivate this article. Its coefficients express, for each group, the degree of conversion of individual or household characteristics, such as income, into residence in a community with low crime. The theory of spatial assimilation leads to three expectations about such models: that the coefficients for socioeconomic and assimilation variables are negative, indicating that increases in these variables improve the ability of individuals to live in low-crime communities; that the coefficients are fairly similar across groups; and that, given a set of specific values for the independent variables, the predicted values from different group-specific equations are approximately equal. The last expectation is tantamount to saying that, once individual-level characteristics are controlled, members of different groups reside in communities with similar crime rates; differences among groups in exposure to crime are largely compositional in nature. The stratification model, on the other hand, leads to two expectations: that the coefficients of socioeconomic and assimilation variables differ across group-specific equations, because it costs some groups more to enter low-crime communities; and that the predictions from different equations for individuals with similar characteristics other than racial/ethnic membership are different and favor the non-Hispanic white majority. The latter expectation is the same as saying that groups are in fact unequal in residential exposure to crime, even when their socioeconomic, assimilation, and other relevant personal characteristics are taken into account. That is, minorities do not live in the same kinds of places as comparable whites.

If this last expectation turns out to be the case, the next question is whether there are other aspects of the locational process for minorities and the majority that may explain any disparities in exposure to crime. For instance, it could be that, as recent suburbanites, minorities tend to be located in suburban communities with high in-migration rates, which are in turn associated with relatively high crime rates (Logan & Messner 1987); or that, because of processes of segregation, they are limited to suburbs with large numbers of poor or minority residents, which also tend to have high crime rates (Roncek 1981; Sampson 1987; Stahura, Huff & Smith 1980). These possibilities suggest an expansion of the analytical model above to include contextual variables among the predictors, as follows:

$$Y_j = a + b_1X_{1ij} + b_2X_{2ij} + b_3X_{3ij} + b_4X_{4j} + \epsilon_{ij}$$

where X_{4j} represents a community-level variable, such as the in-migration rate or the proportion of residents below the poverty line, and the other variables are defined as before. Group differences must then be reassessed to see whether they have been explained to any degree by the contextual variables.

If group differences disappeared, we would conclude that the contextual variables mediate the effects of race. For example, it is plausible that blacks live in higher crime areas than do comparable whites because they are found in lower income suburbs, or suburbs with lower proportions of white residents, than comparable whites. If racial composition itself were the key contextual variable, we could not rule out the possibility that greater black exposure to crime is "only" a by-product of racial residential segregation and, specifically, of the effect of racial composition on crime rates. But it is also possible that contextual variables do not explain the race differences. Then we would conclude that the crime rate of a suburb is itself a source of residential segregation: over and above other aspects of segregation, blacks are steered to places with higher crime rates than those where comparable whites live.

Both of these models have a feature that has made similar models difficult to estimate in the past: they require variables from different levels of aggregation — community and individual. The critical stumbling block, found in much research on spatial processes, is that there is typically no data set in the form required for direct model estimation: individual-level cases with community variables attached.[2] In particular, census data, which offer the most complete geographical coverage as well as a wide array of community and individual characteristics, are available either in an aggregate form or an individual one, forcing past analysts into a choice between the two. The aggregate form, the summary tape files (STFs), allows for distinctions among small geographical units (e.g., census tracts) but does not allow individual records to be linked to them. The alternative, the Public Use Microdata Samples

(PUMS), provides individual-level data but describes their geography only in terms of very large units (counties or county groups), thus precluding insight into community differentiation. For the most part, analysts have chosen the finer spatial distinctions afforded by aggregate census data, thus risking the ecological fallacy in drawing conclusions about the locational processes affecting individuals and households. The magnitude of this risk remains unknown, despite several attempts with unusual data sets to create parallel analyses with both levels of data (e.g., Gross & Massey 1991; Massey & Denton 1985).

Our results in this article are based on a novel method that uses both aggregate- and individual-level data files to construct regression analyses that bridge the two levels of data. This method can be used to analyze locational processes in terms of a wide range of community characteristics, which can appear as dependent as well as independent (contextual) variables. We will only sketch the method here, because it is described at greater length in the Appendix and elsewhere (Alba & Logan 1992, 1993; Logan & Alba 1993). The method derives from a fundamental principle of OLS regression: the estimation of regression coefficients requires only pairwise (i.e., correlations or covariances) and univariate (i.e., means and standard deviations) information for all variables (Hanushek & Jackson 1977). The key element is a matrix of correlations or covariances, and this we construct by combining data from summary tape files and public use samples. In particular, from summary tape files (mainly STF4B) we calculate the correlations between any aggregate and any individual-level variables (see the appendixes for an example). This is straightforward as long as: one can find STF tables that show the distributions of the various individual-level variables by racial/ethnic group in each community;[3] and one is willing to view the aggregate variables as constant within a community. We also use the STF data to calculate correlations between aggregate variables across individuals (these are, in fact, just weighted correlations). From the PUMS data, we calculate the correlations between individual-level variables. It is not necessary to know about the specific communities in which individuals reside to do this, but it is necessary to make the boundaries of the region extracted from the PUMS data coincide quite closely with those mapped by the communities extracted from the STF data.[4]

Once the calculations are done, we assemble the correlations into a matrix. The rows and columns of the matrix pertaining to aggregate variables (correlations among aggregate variables and correlations between aggregate and individual-level ones) come from STF data (to which crime statistics have been added). Those pertaining to individual-level variables come only from the PUMS data. This matrix is then submitted to a regression program (such as that in SPSS-X), along with variable means and standard deviations, and regression coefficients are estimated.

Research Design

SAMPLE

For a research site, our analysis focuses on suburban communities in the New Jersey portion of the New York City Consolidated Metropolitan Statistical Area (CMSA). Practical constraints limit us to the New Jersey portion only. Specifically, we are constrained by the geography of the Uniform Crime Reports (UCR) of the FBI, the source of the crime rate estimates we employ. We are forced to exclude metropolitan counties where reporting local police jurisdictions overlap (true in much of New York State), since some crimes may be multiply reported and, in any event, the overlap makes it impossible to determine the crime rates of specific areas. Within the region we analyze, we equate politically incorporated towns with suburban communities. This is not just a matter of data reporting. Our definition of suburban communities is formulated in terms of jurisdictional boundaries in accordance with the place-stratification model, which views communities as collective actors engaged in a competition to preserve or enhance their advantages. These considerations also help to clarify why we do not include central cities in the analysis. Their much larger average size makes it problematic to treat them as single communities, as we do suburbs. To consider the crime variations among their neighborhoods would require us to obtain both accurate crime data and tables of socioeconomic and other characteristics by major racial/ethnic group. Both requirements pose difficult, if not insuperable, hurdles.

The suburban area under analysis (i.e., the New Jersey side of the CMSA) encompasses 352 suburban towns and cities; and the UCR data report crime tallies for 244 of them. The maps in Figures 1 and 2 indicate the geography of our data and, by identifying the lowest and highest quartiles, give a rough sense of geographical variation in property and violent crime rates. Places considered by the census as central cities are excluded (these are mostly identified on the maps).

As the maps show, the communities under consideration extend from northern New Jersey to its eastern midsection, in an arc abutting New York City (which is not shown). Several of them have long-standing minority populations. For example, the black populations of Orange, East Orange, and Plainfield were already above 20% in 1960, and grew to well over 50% by 1980. Minorities are comparatively new to other communities: Irvington had a negligible black population in 1960, which grew to 38% by 1980. Elizabeth was only 11% black in 1960, but increased to 18% black in 1980, and also had the largest concentration of Hispanics (25%) in 1980. These places are all among the top quartile in our sample of 244 places in both the violent and property crime rate. Asians were a much smaller share of the population, but they did comprise more than 9% of the total in both Fort Lee and Englewood Cliffs by 1980. These suburbs had closer to the median levels of violent and property crime.

The blank areas in the maps, where no crime data appear, fall into one of three types: they are central cities, which are by definition outside the scope of our analysis; they are outside of the CMSA part of New Jersey (true of south and southwest parts of the state); or UCR data are not reported for them. Size of place appears to be the principal determinant of omission from the UCR reports, since smaller towns presumably lack their own police force.[5] The data available for analysis are also affected by the sparse numbers of some groups in some of the communities included in the data, a result of segregation and community size. In such cases, group-specific data may be missing, or "suppressed," in census terminology. Consequently, the specific number of communities varies from group to group, from 217 for non-Hispanic whites to 131 for Asians. Nevertheless, the great majority of each group's members in the New Jersey suburban region is included in the communities we analyze: 79.6% of non-Hispanic whites, 90.0% of non-Hispanic blacks, 82.8% of Hispanics, and 75.9% of Asians.

DATA SOURCES AND VARIABLE DEFINITIONS

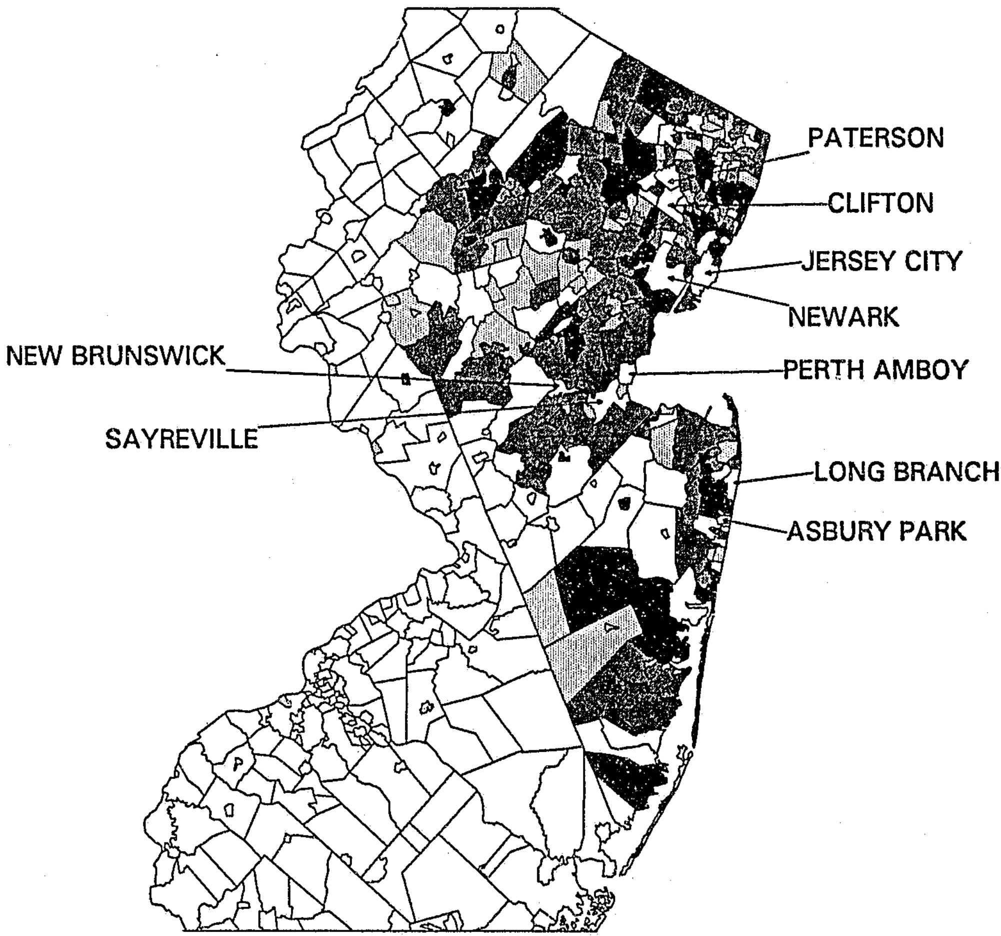
We use several sources of data on New Jersey towns. In addition to the Uniform Crime Report files, we have calculated a variety of other community-level characteristics — e.g., in-migration rates and racial composition — from Summary Tape File 3. Data about characteristics of residents who belong to a particular racial/ethnic group — e.g., the household incomes of black residents of a town — come from Summary Tape File 4B. Finally, from the 5% 1980 PUMS data, we have extracted separate files by group, containing all group members residing in New Jersey suburban, i.e., non-central-city, portion of the New York CMSA. The numbers of cases in these files in effect determine the degrees of freedom for our analysis, because correlations derived from the PUMS data are necessarily based on a smaller number of sampled cases than the correlations derived from the summary tape files. In general, we have limited the number of cases for a group to 10,000 in order to prevent variations in group sizes from influencing significance tests.[6]

The dependent variables in our analysis are indices that have been used in previous studies of suburban crime (Logan & Messner 1987; Stahura, Huff & Smith 1980). These indices generally weight crimes according to their relative frequency; for example, although murder is included in the violent crime rate, its impact on that index is small because the frequency of murder is low. Reliance on reported crime introduces some error into the analysis in that reported crime is considerably lower than the actual incidence of crime. Unfortunately, there is no alternative measure available (e.g., as in victimization surveys) at the community level.

Property Crime Rate

The property crime rate is calculated as a sum of the burglary, larceny, and auto theft rates, each expressed as a rate per 100,000 in population. Correlations among these components range from .48 to .60. The mean property crime rate (weighted by population size) is 5,107, with a standard deviation of 2,339. The range is 343 to 25,582; deleting two cases at each extreme, the range is 1,459 to 12,575.

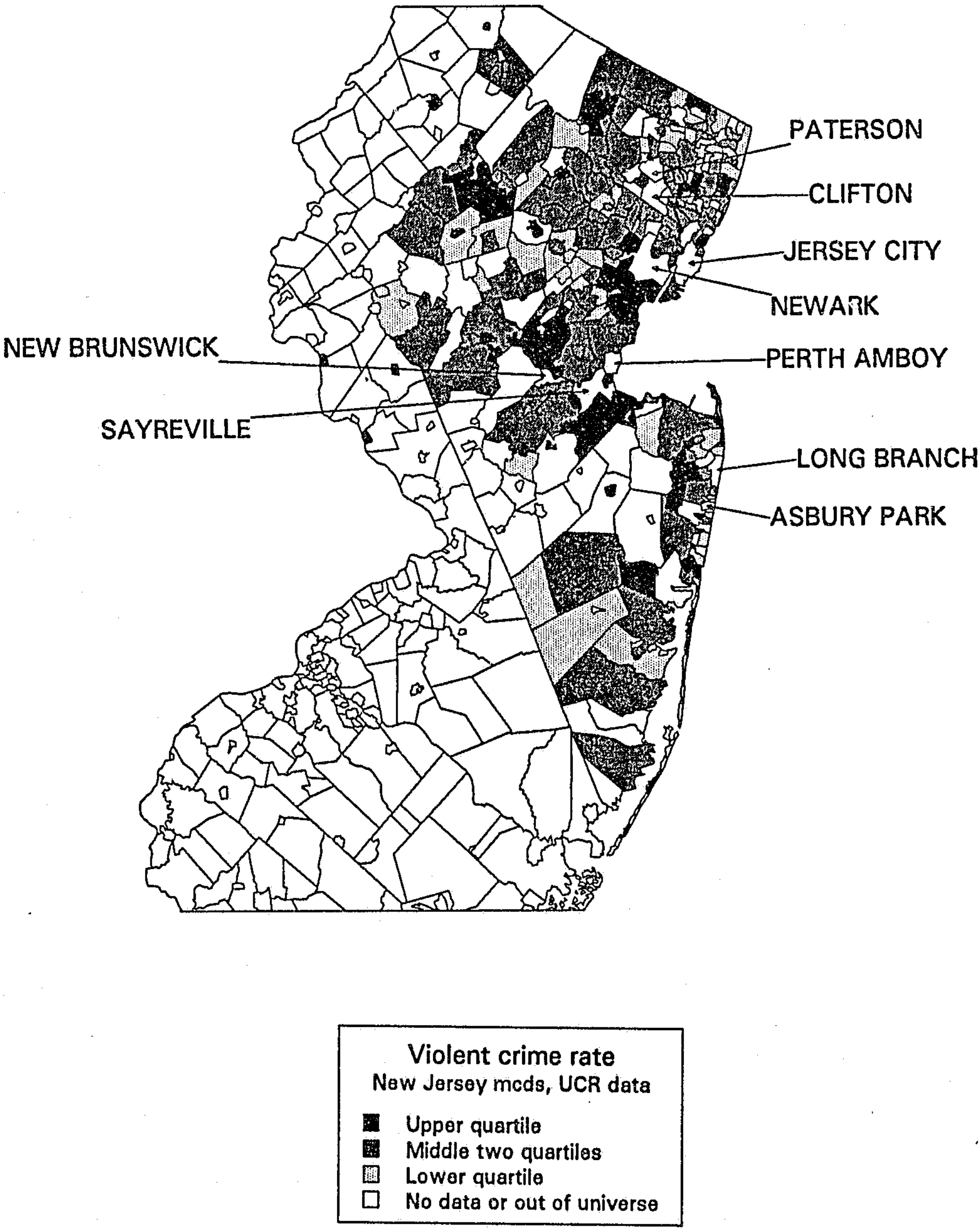
FIGURE 1: Property Crime Rates in New Jersey Suburbs, 1980



Property crime rate
New Jersey mcds, UCR data

- Upper quartile
- Middle two quartiles
- Lower quartile
- No data or out of universe

FIGURE 2: Violent Crime Rates in New Jersey Suburbs, 1980



Violent Crime Rate

The violent crime rate sums the murder, rape, assault, and robbery rates per 100,000 in population. Most correlations among these components range from .37 to .54; however, the murder rate is not significantly correlated with rape or assault. The mean violent crime rate (again weighted by population size) is 991, with a standard deviation of 741. Aside from three small towns with no reported crimes and one with a rate of 9,544, the range is 42 to 3,844.

The individual-level independent variables include a number of demographic, socioeconomic, and assimilation variables characterizing individuals or households. Because of the categorical format of census summary tables, which are pivotal for our data construction, we have represented each independent variable as a set of dummy variables. This construction also has the advantage of giving the intercept a simple, empirically meaningful interpretation (as will become clear in our subsequent discussion). The variables are:

English-language Ability

This assimilation measure consists of three categories: those who speak only English at home, those who speak English well, and those who do not speak English well.

Nativity/Immigration Status

Nativity/immigration status, a second assimilation measure, consists of the categories: U.S. born, arrived before 1975, and arrived 1975 or later.

Household Income

Household income, in 9 categories as reported in census tables, ranges from less than $5,000 per year to $75,000 and above.

Homeownership

Homeownership measures whether or not an individual lives in owner-occupied housing.

Education

Education, in five categories, is defined for individuals at least 25 years old.

Age

Age, in five categories, ranges from younger than 5 years old to 65 and older.

Household Composition

Household composition consists of the following categories: married-couple household; other family household; nonfamily household; and institutional setting, also known as "group quarters."

Ethnic Subgroup

For all groups except blacks, ethnic subgroup represents a series of more specific categories of origin, such as Chinese or Japanese among Asians. Among non-Hispanic whites, the categories include major single ancestry groups: English, French, German, Irish, Italian, and Polish; all other individuals are placed in the residual, omitted category. Among Hispanics, both national origin and racial distinctions are included. One set of categories distinguishes among Mexicans, Puerto Ricans, Cubans, and all others; another among white, black, and other Hispanics. Finally, among Asians, the national origins distinguished are: Chinese, Japanese, Koreans, Filipinos, Asian Indians, and Vietnamese.

Finally, the contextual variables refer to community characteristics that are relevant to suburban crime and also potentially to the distinctive suburban locations of racial/ethnic minorities. The specific indicators selected are indicated below.

Community Population Size

Community population size is expressed as the natural logarithm of the 1980 population. The strongest theoretical link between aggregate population size and interpersonal crimes is provided by Wirth (1938) and Mayhew and Levinger (1976). Wirth, for instance, argues that large population size produces transitory and superficial social relations. The result, according to this view, is a decreased capacity for collective social control throughout the community. This argument is bolstered by recent research that directly links variations in neighborhood social control to victimization rates (cf. Sampson & Groves 1989).

Racial Composition

Racial composition is the percent of residents who are non-Hispanic black (Messner 1983; Sampson 1987; Smith & Jarjoura 1989). An explanatory role for this variable is indicated by theories that link racial composition and rates of community crime. One such theory is the subculture-of-violence thesis (Curtis 1975; Wolfgang & Ferracuti 1967), which argues that high black offending rates for violent crime are the result of a subculture that legitimates and condones violent behavior. Another stresses the importance of structural factors such as racial inequality in socioeconomic conditions (Blau & Blau 1982), black male joblessness, and the prevalence of female-headed households (Wilson 1987; Sampson 1987). For instance, Blau and Blau (1982) argue that socioeconomic inequalities based in ascriptive characteristics such as race give rise to frustration and resentment, which are likely to be manifested in turn in "nonrealistic" violence such as street crime.

Community Poverty Level

Community poverty level is the percent of residents below the poverty line. The connection between poverty and crime has long been recognized by researchers working within the social disorganization or Chicago perspective (Shaw & McKay 1942). On the one hand, poverty weakens the commitment to conventional norms because the universal goal of economic success is not attainable. On the other, it affects the institutional structures of poor neighborhoods because institutions such as churches, which play a role in social control, are weaker where economic rescurces are meager.

In-migration Rate

In-migration rate is the percentage of householders who moved into their unit between 1975 and 1980. The in-migration rate of a community is thought to be an important requisite in the formation of local friendship networks (Kasarda & Janowitz 1974; Sampson 1988) and social relationships more generally (Kornhauser 1978; Sampson & Groves 1989). Weak informal and formal ties to the community may increase crime rates by decreasing the collective social control.

Multifamily Housing

Multifamily housing is the percentage of all housing units in buildings containing more than one unit. Sampson (1987) argues that in densely settled areas, "residents have difficulty recognizing their neighbors and may be less willing to engage in guardianship behavior" (357). Thus, multifamily housing may affect crime rates because it is linked with variation in social control.

To facilitate comparisons of the intercepts among equations where contextual variables are employed, they have been transformed into deviations from their means (across all suburban communities in the region).

Findings: Individual-level Variables

Table 1 shows the average residential crime rates experienced by different racial/ethnic groups in New Jersey suburbs. These averages are to be understood as averages for individuals, not for suburban communities: for each group, they have been calculated by weighting the crime rates for each community by the number of residents from that group. The correlation ratio is also reported to establish the strength of the association between race/ethnicity and crime rate.

The data in the table demonstrate great racial/ethnic disparities in residential exposure to crime, even in suburbs. The disparities are largest for the broad racial/ethnic categories, as opposed to the subgroups they contain, and are larger for the violent crime rate than for the property crime index. In terms of the violent crime rate, the suburban community of the average black is more than twice as hazardous as that of the average white. The community of the average Asian is almost on a par with that of the average white, while that of the average Hispanic falls in between the extremes. There are also substantial differences in the property crime index. The average black lives in a community whose property crime rate is 1.5 times that experienced by the average white. The risk experienced by the average Hispanic is, once again, in between these extremes, while the Asian mean is close to the white mean.

Subgroup differences, although generally significant, are much less impressive. Among whites, the differences are very small. The violent crime rate experienced by the average person of unmixed Polish ancestry stands somewhat above the others; differences in the property crime rate appear quite modest, except for the very small group of single French ancestry. Differences among

TABLE 1: Average Exposure to Property and Violent Crime for Individuals by Racial and Ethnic Group

	Population Total	Exposure to Property Crime	Exposure to Violent Crime
Non-Hispanic whites			
Total and average rates	3,101,342	4,815	876
British	131,031	4,806	863
French	16,694	5,006	913
German	209,376	4,810	848
Irish	248,143	4,760	880
Italian	471,526	4,870	892
Polish	170,717	4,818	990
Other/mixed	1,853,855	4,808	865
Eta-squared (η^2) (subgroups)		.00	.00
Non-Hispanic blacks	292,852	7,537	1,923
Hispanic			
Total and average rates	200,669	6,035	1,430
Mexican	5,089	5,374	1,110
Puerto Rican	64,737	5,825	1,365
Cuban	52,876	6,431	1,631
Other Spanish	77,967	5,984	1,369
Eta-squared (η^2) (subgroups)		.02	.02
White	157,068	5,937	1,400
Black	6,076	6,815	1,657
Other	37,525	6,319	1,521
Eta-squared (η^2) (subgroups)		.01	.01
Asians			
Total and average rates	62,372	5,160	904
Japanese	6,495	5,205	760
Chinese	15,019	4,776	774
Korean	7,460	5,039	853
Filipino	11,071	5,689	1,052
Asian Indian	18,826	5,125	956
Vietnamese	1,346	5,687	1,221
Other Asian	2,155	5,372	989
Eta-squared (η^2) (subgroups)		.02	.03
Eta-squared (η^2) (4 main groups)		.11	.17

TABLE 2: Individual-Level Models of Exposure to Property Crime and Violent Crime[a]

	Property Crime		Violent Crime	
	Coef.	Std. Error	Coef.	Std. Error
Age				
Younger than 5	-2	130	-59	39
5-17	-45	102	-91*	30
18-24	9	109	-52	32
25-64	—		—	
65 and older	-97	80	-66*	24
Household structure				
Married couple	-45	83	-8	24
Other family	-46	96	17	28
Nonfamily	—		—	
Group quarters	-478*	219	-374*	65
Homeownership				
Owner-occupied	-334*	56	-234*	16
Renter	—		—	
Household income				
Less than $5,000	—		—	
$5,000-$9,999	-192	127	-90*	38
$10,000-$14,999	-240	125	-111*	37
$15,000-$19,999	-308*	124	-134*	37
$20,000-$29,999	-338*	118	-146*	35
$30,000-$39,999	-451*	125	-192*	37
$40,000-$49,999	-567*	135	-243*	40
$50,000-$74,999	-611*	140	-288*	42
$75,000 and over	-718*	172	-386*	51

Asian groups are more substantial. The average Chinese and Japanese reside in communities that are safer, in terms of violent crime, than that of the average white (of any group); Filipinos and Vietnamese are in more crime-prone communities. The differences in property crime rate are less salient among these groups, although the average Chinese suburbanite is found again to be located in a relatively low-crime community, on a par with that of the average white. The largest subgroup differences occur, as expected, for the Hispanic groups. Paralleling differences in community resources we have found in other analyses (Logan & Alba 1993), Cubans experience the highest residential crime rates, Mexicans the lowest; Puerto Ricans are in the middle. Differences by race among Hispanics are almost as large, with black Hispanics experiencing crime on a par with Cubans, while white Hispanics experience lower crime rates. However, the racial subgroups of Hispanics do not approximate non-Hispanic whites and blacks — the average black Hispanic is exposed to lower crime rates

TABLE 2: Individual-Level Models of Exposure to Property Crime and Violent Crime[a] (Continued)

	Property Crime		Violent Crime	
	Coef.	Std. Error	Coef.	Std. Error
Education				
Grammar school	—		—	
Some high school	6	108	-18	32
High school graduate	-2	94	-60*	28
Some college	-30	112	-105*	33
College graduate	-104	106	-148*	32
English language ability				
Only English	—		—	
Speaks English well	106	79	74*	23
Does not speak English not well	399*	155	230*	46
Immigration status				
U.S. born	—		—	
Arrived pre-1975	171	87	45	26
Arrived 1975 or later	172	185	34	55
Race and ethnicity				
Non-Hispanic white	—		—	
Non-Hispanic black	2,532*	84	927*	25
Hispanic	880*	105	369*	31
Asian	129	184	-60	55
Other	967	527	307	158
Intercept	5,495*	142	1,295*	42
R^2	.12		.21	
Adjusted R^2	.12		.21	

[a] Unstandardized regression coefficients
— Indicates omitted category
* p < 05

than the average non-Hispanic black, while the average white Hispanic is exposed to higher rates than the average non-Hispanic white.

Table 2 allows us to see whether the gross racial/ethnic disparities can be explained in a simple fashion by compositional, i.e., individual-level, differences among groups and also serves as an introduction to our locational-analysis strategy. The table presents locational models estimated for the entire suburban population. That is, based on the method described earlier, we have estimated regression models in which the two crime rates appear as dependent variables and such individual characteristics as race/ethnicity, age, household type, income, and education constitute the independent variables. In this model, unlike subsequent ones, we are assuming that income, household type, and other such variables have the same effects on residential exposure to crime for the members of different racial/ethnic groups. Nevertheless, substantial amounts of individual-to-individual variation in residential exposure to crime are explained, especially in the case of violent crime ($R^2 = .21$).[7]

The table demonstrates that some of these variables do have pronounced effects on residential exposure to crime. This is true, in particular, of the socioeconomic variables. Owning a home, for instance, enables individuals to live in safer communities. According to the coefficients in the table, home owners reside in communities whose violent crime rates are nearly 250 (per 100,000) units lower than the rates in the communities in which comparable renters are found. In terms of property crime, the net effect of homeownership is to lower residential exposure by nearly 350 (per 100,000). It is also apparent that high household income (especially $50,000 or more) enables individuals to avoid communities with high crime rates. College education plays an additional role in the case of the violent crime rate.

To put the effects of the socioeconomic variables into perspective, it is useful to take the intercept as a reference point. Because of the categorical construction of the independent variables, the intercept is unusually informative here, for it represents the predicted crime rate in the community of residence for an individual who is in the omitted categories of all the independent variables (i.e., a native-born, English-speaking person between ages 25 and 64, who lives in a nonfamily, renter household with less than $5,000 in annual income, did not go beyond the 8th grade, and in the case of race/ethnicity, is non-Hispanic white). In socioeconomic terms, the posited individual is disadvantaged, and accordingly the model predicts that he or she resides in a community with a violent crime rate of 1,295 (per 100,000), well above average. Against this standard, the combined effects of the socioeconomic variables are quite substantial. A homeowner ($b = -234$) with a 1979 household income between $50,000 and $74,999 ($b = -288$) and a college degree ($b = -148$) would live in a community whose violent crime rate is only half as high (625 per 100,000). The same characteristics would reduce residential exposure to property crime more modestly, by about a fifth.

Other variables that represent possible compositional differences among racial/ethnic groups are not nearly as powerful. Age has small effects on exposure to violent crime, none on exposure to property crime. Household type has no impact, except for the unusual case of residence in an institutional setting, which lowers exposure to crime (presumably because such institutions as college dormitories, nursing homes, and even prisons tend to be in more crime-free communities). Nativity and immigration status also have no effects. The most noteworthy of all these effects is associated with language: not speaking English well raises exposure to crime.

Yet even with socioeconomic characteristics controlled, the disparities between whites and both blacks and Hispanics remain large (the dummy variable representing Asians is not statistically significant in either equation). In the equation for the violent crime rate, the net difference between comparable non-Hispanic blacks and whites (the latter form the omitted category) is estimated to be 927 (per 100,000), only a slight reduction from the gross difference of 1,047 in Table 1. The proportional reduction is even smaller for the property crime rate. The proportional reductions are somewhat larger for the Hispanic-white comparison, but Hispanics are still likely to live in communities with substantially higher crime than are comparable non-Hispanic whites. In absolute magnitude, the black-white differences clearly exceed those associated with socioeconomic variables, while the Hispanic-white differences rival them.

If such large racial/ethnic differences remain even when compositional differences among groups are controlled, the next question is whether the socioeconomic and other determinants of residence work in the same way for the members of different racial/ethnic groups. Could it be that whites gain more in safety from high income (or other characteristics) than do blacks or Hispanics? Or, alternatively, could it be that high-income minorities avoid crime-ridden communities and thus catch up with their white peers to a degree that the results in Table 2 cannot show? Tables 3 and 4, which present locational models estimated separately for each group, allows us to address these questions. The table yields one immediate sign of the relative power of racial/ethnic differences: The equations in the table represent within-group analyses, and their R^2 values are much lower than those in Table 2 because race/ethnicity is no longer a predictor. In Tables 3 and 4 the coefficients for minority group members that are significantly different from those for non-Hispanic whites are indicated by a crosshatch (#) next to the standard error.[8]

Because these analyses permit the effects of individual-level variables to vary across groups, they speak to the differences between spatial assimilation and place stratification that motivate the entire analysis. Overall, the analyses appear to indicate that the characteristics that most powerfully reduce the exposure to crime — homeownership and high income — work in broadly similar fashion among the groups. Such a finding is consistent with spatial assimilation theory.

This result does not mean, however, that the effects of these characteristics are the same in every case across the groups. In some instances, minorities gain more from socioeconomic advantages, but not enough to catch up with whites. This point holds with special force for non-Hispanic blacks, for whom a high income is more effective in facilitating residence in a suburb with a low violent crime rate than it is for whites. At the highest income levels, the improvement experienced by blacks with incomes of $75,000 per year or more (592 per 100,000 in the crime rate) is roughly twice the improvement by whites in this income category (269 per 100,000). But even the most highly educated black homeowner with the highest income has a predicted exposure to violent crime no better than that of the least educated white renter with the lowest income. The existence of such disparities in the residential exposure to crime, even for minorities with high individual attainments, bolsters place-stratification theory, which predicts that people are sorted into places on the basis of group membership.

Another key socioeconomic variable, homeownership, has effects that are more consistent across the groups. It is the only variable that is significant in all eight equations, and the magnitudes of its coefficients are generally quite similar. The only exception is the unusually large reduction in exposure to

TABLE 3: Individual-Level Models of Exposure to Property Crime by Racial/ Ethnic Group

	Non-Hispanic Whites		Non-Hispanic Blacks		Hispanics		Asians	
	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error
Age								
Younger than 5	-76	129	249*	126	518*	105#	-727*	251#
5-17	-91	100	165	103	212*	72#	-344	222
18-24	-39	106	199	111	137	77	-271	252
25-64	—		—		—		—	
65 and older	-81	75	-130	111	-213*	99	-124	230
Household structure								
Married couple	-102	80	-128	81	8	77	-17	163
Other family	-78	96	22	84	-12	86	-85	206
Nonfamily	—		—		—		—	
Group quarters	115	216	-2,312*	189#	-906*	214#	875*	443
Homeownership								
Owner-occupied	-281*	56	-214*	55	-243*	47	-449*	91
Renter	—		—		—		—	
Household income								
Less than $5,000	—		—		—		—	
$5,000-$9,999	-80	131	-135	99	71	80	167	281
$10,000-$14,999	-144	128	-139	97	14	81	-40	270
$15,000-$19,999	-186	125	-168	100	126	81#	312	283
$20,000-$29,999	-214	119	-112	93	153*	78#	14	242
$30,000-$39,999	-295*	124	-293*	107	-130	90	-161	250
$40,000-$49,999	-367*	132	-578*	135	-488*	111	-455	261
$50,000-$74,999	-419*	136	-648*	156	-451*	126	-226	274
$75,000 and over	-538*	164	-1,026*	362	-968*	215	171	307#
Education								
Grammar school	—		—		—		—	
Some high school	1	104	98	112	158	85	52	300
High school graduate	-34	91	200*	100	5	70	-135	225
Some college	-74	108	61	119	-13	94	-80	240
College graduate	-145	102	-24	129	-124	99	-464*	210
English language ability								
Speaks only English	—		—		—		—	
Speaks English well	100	82	-151	136	398*	64#	-99	116
Does not speak English well	237	200	105	372	658*	81	-166	162

TABLE 3: Individual-Level Models of Exposure to Property Crime by Racial/ Ethnic Group (Continued)

	Non-Hispanic Whites		Non-Hispanic Blacks		Hispanics		Asians	
	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error
Immigration status								
U.S. born	—		—		—		—	
Arrived pre-1975	92	91	187	122	254*	64	-7	122
Arrived 1975 or later	186	262	-7	178	460*	85	-78	125
Ethnicity among whites								
British	-21	107						
French	118	290						
German	-38	87						
Irish	-57	80						
Italian	2	62						
Polish	-26	95						
Other singles and mixed	—							
Ethnicity among Hispanics								
Mexican					-366*	132		
Puerto Rican					-78	59		
Cuban					381*	54		
Other Spanish					—			
Race among Hispanics								
White					—			
Black					1,066*	116		
Other					364*	52		
Ethnicity among Asians								
Japanese							39	232
Chinese							-433*	209
Filipino							-79	220
Korean							513*	213
Asian Indian							-180	204
Vietnamese							520	317
Other Asian							—	
Intercept	5,395*	141	7,841*	123#	5,351*	124	6,189*	375#
R^2	.01		.03		.07		.05	
Adjusted R^2	.01		.03		.07		.04	

Significantly different from coefficient for non-Hispanic whites.
— indicates omitted category

* $p < .05$

property crime accruing to Asian homeowners.[9] Education, by comparison, has the most limited role among the socioeconomic variables. Its effects are, nevertheless, rather consistent when it comes to exposure to violent crime. Regardless of racial/ethnic group, the college educated have lower residential exposure to violent crime than others. But, generally speaking, these effects are modest and similar across the groups; therefore, as is true also of the effects of homeownership, they do not have much effect on group disparities. Only the effect of education on Asian exposure to property crime stands out in this respect. In this case, the reduction in exposure among college educated members of the group is quite large, though not significantly different from that for whites.

Apart from the socioeconomic variables just described, no other variables in our models have effects that are consistent across the groups. The remaining effects of importance largely indicate subgroup variations that qualify in noteworthy ways the differences that separate whites from Hispanics and Asians. This role can be seen in the case of the assimilation variables, nativity, and English proficiency. These variables have substantial and statistically significant effects among Hispanics; effects are only scattered for other groups. Hispanics who are less linguistically assimilated reside in communities with higher crime rates, as is true also for those who were born outside the U.S. and have recently immigrated. The combined magnitude of these effects rivals those of socioeconomic status and implies great variability in Hispanic exposure to crime according to assimilation status. Also relevant are the national origin and race of Hispanics. Hispanics present a consistent profile of intragroup differences: Cubans are more residentially exposed to crime, whether against property or persons, than other Hispanic national-origin groups. So are black and other nonwhite Hispanics. (For property crime only, Mexicans are less exposed than other groups.) The magnitudes of some of these differences, especially by race, are quite large.

Accordingly, the difference in residential exposure between non-Hispanic whites and Hispanics depends very much on the characteristics of the Hispanics. The intercepts for whites and Hispanics are no different; the disparity found in Table 1 disappears entirely when we control for background characteristics and for the strong negative effect among Hispanics of not speaking English well. Therefore for some Hispanic subgroups, residential exposure to crime is no worse than for comparable non-Hispanic whites. This statement holds specifically for Hispanics who are white, English-speaking, U.S.-born, and non-Cuban. But deviations from these characteristics tend to worsen the comparison for Hispanics. The disparity in exposure to crime is especially severe for black Hispanics or recent immigrants who do not speak English well. Nonetheless, a comparison to the equations for non-Hispanic blacks indicates that even black Hispanics reside in safer communities than African Americans.

Subgroup variations are not as consequential among Asians. In fact, the assimilation variables have no impact on Asians; Asian suburban location depends principally on socioeconomic status, rather than assimilation (see also Alba & Logan 1993; Logan & Alba 1993). But there are differences by national origin. The Chinese are less exposed to crime, by either index, than other groups, while the Koreans are more exposed. In terms of exposure to violent crime, the Japanese are significantly advantaged, while the Vietnamese are significantly disadvantaged; neither group is distinctive when it comes to property crime. As with Hispanics, these variations can be seen as modifying the white-Asian comparison. In this case, the difference in the intercepts is larger than that in the raw mean scores: for instance, while the difference in the means for the property crime index was just 4,815 (for whites) versus 5,160 (for Asians), that in the intercepts is 5,395 versus 6,189. The Asian intercepts refer to the "other Asian" category and would be different if other national-origin categories were posited instead — for instance, smaller if the comparison were based on the Chinese and larger if based on Koreans.

In summing up a somewhat complex story line, one point stands out: Blacks have a uniquely high exposure to crime. Controlling for other individual-level characteristics and allowing their effects to vary by group has done little to reduce the gap between blacks and others in exposure to crime. If anything, the apparent gap has grown, because the relative position of Hispanics shifts closer to that of whites when socioeconomic status and assimilation level are controlled. The analysis reiterates, moreover, that the disparity between whites and Hispanics is due in part to the presence of blacks in the Hispanic group, underscoring the unique locational disadvantages associated with black skin.

Contextual Effects

We turn now to contextual predictors. The rationale for their inclusion stems from the fact that crime rates are but one dimension of communities relevant for locational sorting processes. These processes distribute individuals, based in part on their racial/ethnic backgrounds, into communities that differ in other characteristics, too. We are especially interested in identifying the origin of the black-white disparities that cannot be explained by differences at the individual level. Are blacks specifically steered into high-crime communities, or is their greater exposure to crime a by-product of their residence in suburbs that are distinctive in some other respect that we can identify here? If the latter is true, then once the other community characteristics are taken into account, the differentials in crime exposure should be explained. In resorting to contextual predictors, we are not simply reinventing the ecological models of past research. Contextual variables are introduced here as control variables in models that are formulated at the individual level.

Especially critical here are processes of racial/ethnic and income segregation. It is known that black suburbanites reside in communities with higher minority proportions and lower average household incomes than do similar whites (Alba & Logan 1993; Logan & Alba 1993; Massey & Denton 1987). In a somewhat related vein, Asians and Hispanics may be more likely than others to reside in suburbs where a relatively high proportion of residents are recent in-migrants. Insofar as the racial composition, average income, or the rate of in-migration of a community is associated with the crime rate, differentials in exposure to crime would necessarily result. But to test for such effects we must include contextual variables in the individual-level equations. It is also important to add population size, to control for sample selection bias (Berk 1983).

We introduce the contextual variables in two stages, based upon our examination of alternative specifications, which showed the contextual variables to be multicollinear. First, we enter three contextual variables — the percent of a community's residents who are non-Hispanic black, the percent who are below the poverty line, and community size (logged) — into the equations of Tables 3 and 4. The resulting regressions are reported in the main body of Tables 5 and 6. Then, we enter two additional contextual variables — the percent of residents who moved into their household between 1975 and 1980 and the percent of housing in multifamily units. The coefficients of these variables, and the R^2 of the equations containing them, are reported in the bottom panel of Tables 5 and 6.

A comparison of the results of the two stages indicates that racial composition, community poverty, and community size capture the lion's share of the contextual variation in exposure to crime. Indeed, a comparison of the R^2s after these three variables have been introduced to the R^2s attained by individual-level variables only (in Tables 3 and 4) shows that these contextual variables explain a good deal of individual variation in exposure to crime within each racial/ethnic group. For property crime, the R^2s in Table 5 vary from .24 (for whites) to .49 (for Hispanics), and they are even larger for violent crime. However, little further improvement occurs by adding the remaining two contextual variables. Moreover, these two variables frequently are not statistically significant or have coefficients not in the predicted direction (e.g., increases in in-migration often lower exposure to crime).

Accordingly, we conclude that the models with only racial composition, community poverty, and community size are superior for interpretive purposes. According to their coefficients, these three contextual variables exert generally consistent and sizable effects on exposure to crime: living in a suburb with a relatively high percentage of black and/or poor residents lifts the risk of crime victimization substantially, as does living in a larger (and presumably more urban) suburb.[10] However, the profile of these contextual effects differs somewhat between the two crime types. For property crime, the dominant effect is generally that associated with racial composition; this is clearer in the standardized coefficients (which are not presented in the table) than in the unstandardized ones, because of the very different scale of the logged population size variable.[11] For crime against persons, the unstandardized effect of community poverty rate is larger, although the effects of poverty and racial composition are more nearly equal when measured by standardized coefficients. There are also significant intergroup variations in their magnitudes for which we have no ready explanation; because these display no clear-cut pattern, we do not dwell upon them here.

Despite these variations in the nature of the contextual effects, there are other consistencies to indicate that the contextual variables play an important role in explaining individual-level patterns in exposure to crime. For one thing, few significant individual-level effects remain once the contextual variables are present in the equations; and of those that do, some have had their signs reversed from Tables 3 and 4. The latter is true of ownership in the white and black equations for property crime, for instance. Of the remaining individual-level effects, the most meaningful appear to be associated with subgroup membership and assimilation status among Hispanics. It remains true that Cubans, the foreign born, and those who do not speak English well are worse off than other Hispanics. Note, however, that with the contextual variables controlled, black Hispanics are less exposed to crime than others, a reversal of the finding from Tables 3 and 4.

A second consistency is the reduction of the differences among the racial/ethnic groups in exposure to crime in the equations containing the contextual variables, although we must also emphasize that not all differences are eliminated. This reduction can be observed in the intercepts, which impose a standardized community context on all the groups. As we noted in the last section, a comparison of intercepts is instructive because the values of individual-level variables are held constant (at the omitted categories of all variables). So, for the equations in Table 5, are the values of the contextual variables (their zero points have been set at the means for all the suburban communities). According to these intercepts, the differences observed in earlier tables that favored whites over Asians and Hispanics have been explained. The intercepts for Hispanics are now below those of whites; even though these intercepts describe only some subgroups of Hispanics, the remaining disadvantages borne by other subgroups — e.g., Cubans, poor English speakers — are not large enough to overturn the basic parity. And the Asian intercepts are essentially tied with those of whites.

Blacks remain a somewhat singular group. Their distance from whites and other groups has been reduced but not eliminated by the contextual controls. It is important to note here that the reduction is not due only to the inclusion of racial composition as a predictor. If so, as noted above, one could not rule out the possibility that the black disadvantage is just a reflection of the higher crime rates in heavily minority communities. But this is not the whole story. With context controlled, blacks are only slightly above whites in exposure to violent crime — a dramatic reduction compared to the racial differences in earlier tables — but this reduction is mostly due to the poverty variable. A greater difference remains in terms of property crime, where racial composition played a stronger role in the contextual model. Here the white/black difference is about half the size in Tables 5 and 6 of what it was in the preceding tables.

The intercepts in Tables 5 and 6 assume that all groups are placed in "average" suburbs (i.e., suburbs with the mean values on the contextual variables). These resemble the suburbs in which the average white resides. However, the differences in exposure to property crime are essentially eliminated if all groups are placed in the context of the average black.[12] In this case, the predicted crime rate to which a black in the omitted categories is exposed (7,530) is less than that predicted for a similar white (7,915) and for an Asian or Hispanic (7,843 and 8,062, respectively). For violent crime, calculations such as these lead to a similar conclusion. They thus bolster the main conclusion implicit in the contextual analysis: even controlling for individual-level differences, the distinctive locational process for blacks places them in more urban suburbs with disproportionately large numbers of minorities and the poor, resulting in higher exposure to crime. Comparable whites, if located in the same kinds of communities, would face the same outcome.

TABLE 4: Individual-Level Models of Exposure to Violent Crime by Racial/Ethnic Group

	Non-Hispanic Whites		Non-Hispanic Blacks		Hispanics		Asians	
	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error
Age								
Younger than 5	-88*	35	79	49#	270*	42#	-255*	67#
5-17	-108*	27	39	39#	79*	29#	-156*	59
18-24	-69*	29	66	43#	53	31#	-92	67
25-64	—		—		—		—	
65 and older	-47*	20	-113*	43	-85*	40	-28	61
Household structure								
Married couple	-43	22	-38	31	8	31	5	43
Other family	-1	26	17	32	9	35	0	55
Nonfamily	—		—		—		—	
Group quarters	-151*	59	-1,012*	73#	-359*	87#	35	118
Homeownership								
Owner occupied	-204*	15	-239*	21	-165*	19	-252*	24
Renter	—		—		—		—	
Household income								
Less than $5,000	—		—		—		—	
$5,000-$9,999	-25	36	-57	38	31	32	-47	75
$10,000-$14,999	-39	35	-120*	37	1	33	-102	72
$15,000-$19,999	-50	34	-133*	38	30	33	-112	75
$20,000-$29,999	-57	32	-143*	36	53	31#	-161*	65
$30,000-$39,999	-93*	34	-202*	41#	-32	36	-179*	67
$40,000-$49,999	-129*	36	-296*	52#	-176*	45	-326*	70#
$50,000-$74,999	-173*	37	-335*	60#	-309*	51#	-296*	73
$75,000 and over	-269*	45	-592*	140#	-325*	87	-383*	82
Education								
Grammar school	—		—		—		—	
Some high school	-18	28	55	43	54	34	-8	80
High school grad.	-70*	25	58	38#	-12	28	-50	60
Some college	-119*	29	-1	46#	-71	38	-75	64
College graduate	-159*	28	-130*	50	-161*	40	-173*	56
English language ability								
Speaks only English	—		—		—		—	
Speaks English well	69*	22	6	52	207*	26#	-42	31#
Does not speak English well	194*	55	365*	144	329*	32#	-74	43#

TABLE 4: Individual-Level Models of Exposure to Violent Crime by Racial/Ethnic Group for Violent (Continued)

	Non-Hispanic Whites		Non-Hispanic Blacks		Hispanics		Asians	
	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error
Immigration status								
U.S. born	—		—		—		—	
Arrived before 1975	2	25	-10	47	113*	26#	-6	32
Arrived 1975 or later	56	72	-2	69	154*	34	-27	33
Ethnicity among whites								
British	3	29						
French	7	79						
German	-34	24						
Irish	10	22						
Italian	-15	17						
Polish	93*	26						
Other singles and mixed	—							
Ethnicity among Hispanics								
Mexican					-101	53		
Puerto Rican					19	24		
Cuban					215*	22		
Other Spanish					—			
Race among Hispanics								
White					—			
Black					335*	47		
Other					95*	21		
Ethnicity among Asians								
Japanese							-204*	62
Chinese							-154*	56
Filipino							-51	59
Korean							112*	57
Asian Indian							-7	54
Vietnamese							285*	84
Other Asian							—	
Intercept	1,222*	38	2,194*	48#	1,126*	50	1,494*	100#
R^2	.06		.06		.09		.12	
Adjusted R^2	.06		.05		.09		.12	

Significantly different from coefficient for non-Hispanic whites.
— Indicates omitted category

* $p < .05$

TABLE 5: Models with Contextual Variables for Exposure to Property Crime by Racial/Ethnic Group

	Non-Hispanic Whites		Non-Hispanic Blacks		Hispanics		Asians	
	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error
Age								
Younger than 5	-7	114	42	93	171*	78	-303	218
5-17	17	88	33	76	97	53	-107	192
18-24	11	94	17	82	99	57	-135	219
25-64	—		—		—		—	
65 and older	-158*	66	-91	82	-85	73	-142	199
Household structure								
Married couple	17	71	23	60	-14	57	114	141
Other family	-33	84	64	62	-10	64	-74	179
Nonfamily	—		—		—		—	
Group quarters	308	191	-379*	142#	-388*	160#	1,092*	385
Home ownership								
Owner-occupied	145*	50	95*	41	-17	36#	-20	82
Renter	—		—		—		—	
Household income								
Under $5,000	—		—		—		—	
$5,000-$9,999	-13	115	-73	73	103	59	409	244
$10,000-$14,999	-49	112	-21	71	71	60	46	235
$15,000-$19,999	-48	110	35	74	208*	61#	328	246
$20,000-$29,999	-56	105	56	68	164*	58	185	212
$30,000-$39,999	-104	109	-63	79	-10	67	46	219
$40,000-$49,999	-139	117	-163	100	-97	83	-63	229
$50,000-$74,999	-153	120	-254*	116	-146	95	58	240
$75,000 and over	-246	145	-108	268	-520*	160	610*	268#
Education								
Grammar school	—		—		—		—	
Some high school	-13	92	-5	83	50	63	119	260
High school graduate	14	80	-26	74	5	52	-139	195
Some college	14	95	-118	87	25	70	8	208
College graduate	-56	90	-19	95	-24	74	-209	182
English language ability								
Speak only English	—		—		—		—	
Speak English well	-58	72	-34	100	73	48	49	100
Does not speak English not well	-132	176	-122	275	205*	61	102	140
Immigration status								
U.S. born	—		—		—		—	
Arrived pre-1975	31	80	56	90	126*	47	-28	106
Arrived 1975 or later	24	230	-199	131	286*	63	-85	108

TABLE 5: Models with Contextual Variables for Exposure to Property Crime by Racial/Ethnic Group (Continued)

	Non-Hispanic Whites		Non-Hispanic Blacks		Hispanics		Asians	
	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error
Ethnicity among whites								
British	-54	95						
French	20	255						
German	-4	76						
Irish	-88	70						
Italian	-22	54						
Polish	-150	83						
Singles and mixed	—							
Ethnicity among Hispanics								
Mexican					-162	98		
Puerto Rican					-181*	44		
Cuban					388*	41		
Other Spanish					—			
Race among Hispanics								
White					—			
Black					-320*	87		
Other					-35	39		
Ethnicity among Asians								
Japanese							355	201
Chinese							-210	181
Korean							168	191
Filipino							153	185
Asian Indian							-43	275
Vietnamese							-172	177
Other Asian							—	
Community characteristics								
Racial composition	66*	2	51*	1#	76*	1#	71*	2
Poverty level	89*	6	44*	6#	24*	2#	32*	8#
Population size	369*	24	-171*	35#	570*	22#	376*	48
Intercept	4,290*	270	5,693*	359#	4,160*	237	4,407*	581
R^2	.24		.47		.49		.29	
Adjusted R^2	.23		.47		.49		.28	
Other community characteristics								
In-migration rate	-7*	2	4	3#	54*	2#	-1	5
Multifamily housing	-17*	1	3*	1#	-3*	1#	-9*	2#
R^2	.26		.47		.51		.29	

Significantly different from coefficient for non-Hispanic whites.
— Indicates omitted category   * $p < .05$

TABLE 6: Models with Contextual Variables for Exposure to Violent Crime by Racial/Ethnic Group

	Non-Hispanic Whites		Non-Hispanic Blacks		Hispanics		Asians	
	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	S.E. Error
Age								
Younger than 5	-50	26	-5	29	80*	29#	-52	46
5-17	-53*	20	-1	23	35	20#	-36	40
18-24	-35	22	-1	25	44*	21#	-16	46
25-64	—		—		—		—	
65 and older	-71	15	-42	25	-20	28	-27	42
Household structure								
Married couple	-2	16	28	18	-14	22	40	30
Other family	11	19	28	19	-11	24	-23	38
Nonfamily	—		—		—		—	
Group quarters	-6	44	39	44	-11	61	190*	81#
Homeownership								
Owner-occupied	-10	11	14	13	-3	13	-24	17
Renter	—		—		—		—	
Household income								
Less than $5,000	—		—		—		—	
$5,000-$9,999	3	27	-8	22	42	22	115*	51
$10,000-$14,999	6	26	-25	22	40	23	-12	49
$15,000-$19,999	19	26	-13	23	104*	23#	-23	52
$20,000-$29,999	27	24	-17	21	105*	22#	-1	44
$30,000-$39,999	12	25	-16	24	66*	25	14	46
$40,000-$49,999	-3	27	-18	31	53	31	-55	48
$50,000-$74,999	-32	28	-54	36	-81*	36	-65	50
$75,000 and over	-116*	34	-99	83	-74	61	-89	56
Education								
Grammar school	—		—		—		—	
Some high school	-16	21	9	25	13	24	40	55
High school graduate	-35	18	-13	23	18	20	-20	41
Some college	-66*	22	-40	27	-18	27	-12	44
College graduate	-102*	21	-64*	29	-68*	28	-36	38
English language ability								
Speaks only English	—		—		—		—	
Speaks English well	0	16	24	31	15	18	0	21
Does not speak English not well	27	41	128	86	58*	23	16	29
Immigration status								
U.S. born	—		—		—		—	
Arrived pre-1975	-20	19	-49	28	47*	18#	-7	22
Arrived 1975 or later	-7	54	-79	41	85*	24	-32	22

TABLE 6: Models with Contextual Variables for Exposure to Violent Crime by Racial/Ethnic Group (Continued)

	Non-Hispanic Whites		Non-Hispanic Blacks		Hispanics		Asians	
	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error
Ethnicity among whites								
British	-20	22						
French	-33	59						
German	-25	18						
Irish	-11	16						
Italian	-32*	12						
Polish	57*	19						
Singles and mixed	—							
Ethnicity among Hispanics								
Mexican					7	37		
Puerto Rican					-74*	17		
Cuban					123*	15		
Other Spanish					—			
Race among Hispanics								
White					—			
Black					-211*	33		
Other					-53*	14		
Ethnicity among Asians								
Japanese							-70	42
Chinese							-68	38
Korean							37	40
Filipino							-21	39
Asian Indian							-32	37
Vietnamese							101	58
Other Asian							—	
Community characteristics								
Racial composition	19*	.5	7*	.3#	25*	.4#	20*	.5
Poverty level	66*	1	102*	1#	24*	1#	43*	1#
Population size	15*	5	-63*	11#	357*	8#	113*	10#
Intercept	892*	63	1,095*	359	412*	90#	720*	123
R^2	.47		.67		.56		.59	
Adjusted R^2	.47		.67		.56		.59	
Other community characteristics								
In-migration	-8*	.6	-26*	1#	-8*	1	2	1#
Multifamily housing	0	.2	1*	.4#	2*	.3#	-0	.4
R^2	.48		.68		.56		.59	

\# Significantly different from coefficient for non-Hispanic whites
— Indicates omitted category * $p < .05$

Discussion and Conclusion

Our investigation has turned up sizable racial/ethnic disparities in residential exposure to crime, even in suburbia. The increase in suburban crime is not only reinforcing the hierarchy among suburban communities as desirable places to live, but it is differentially affecting racial/ethnic groups. By implication, as minorities leave cities for seemingly safer suburbs, their experience will not equal that of comparable whites. In the region under study, whites and some Asian groups tend to be in the safest communities, while blacks are in the least safe communities. Hispanics fall in the middle. Racial/ethnic differences are, moreover, larger for violent crime than for crime against property.

The significance of community crime rates is broader than the risk of victimization. To be sure, they are indicators of this risk since most crime occurs in the vicinity of, if not in, the victim's home. However, as community-wide characteristics, these rates mask neighborhood-level variations that probably come closer to the risks that individuals actually experience. Nevertheless, differences in crime among communities undoubtedly correspond with other differences that make them more or less desirable as places to live (Stark 1987). A high-crime suburb may be more likely to have a dilapidated residential or commercial section, a visible homeless population, or crime in its schools. Further, high crime in and of itself is likely to cause some more affluent residents to leave or to divert some potential in-migrants to safer communities, thus affecting the relative position of a community in the hierarchy of places.

Race/ethnicity is not the only characteristic that affects the kind of community in which an individual resides. The key to what we have accomplished here is that we are able to estimate an individual-level model with a locational outcome as its dependent variable and thus to investigate directly the mapping of individuals into communities in accordance with their social characteristics. Aside from race/ethnicity, these effects are largely in accord with the expectations of spatial assimilation theory. This is especially the case for socioeconomic variables: high household income and homeownership both afford entry to communities with lower crime rates for members of all groups. Assimilation measures, such as English-language proficiency, are important principally for Hispanics. Although some of the effects we have found could be anticipated from previous ecological research on crime, they could not be directly verified at the ecological level.

Controls for these individual characteristics do explain the white/Hispanic disparity in exposure to crime: the unadjusted differences found in Table 1 are reduced in Table 2 where compositional differences are controlled, and they disappear in Tables 3 and 4 where the especially large effect of poor English language ability for Hispanics is considered. This changes somewhat the relative ordering of groups. Whites appear as advantaged as ever, but now they are joined by some categories of Hispanics (especially those who are white, non-Cuban, and U.S.-born English speakers). When their socioeconomic characteristics are taken into account, Asians are somewhat more exposed to crime than whites. But blacks remain, by far, the group most exposed to crime in suburbs. The far greater exposure of suburban blacks cannot be explained on the grounds that blacks have lower average incomes than members of other groups or differ from them on other personal or household characteristics (of those we have been able to control). In fact, even the most affluent blacks are not able to escape from crime, for they reside in communities as crime-prone as those housing the poorest whites. This finding, it should be underscored, could not have been deduced directly from previous research on ecological research.

Much of the differential for blacks and all the differential for Asians appears to be due to the locational processes that tend to concentrate them in certain types of communities. This conclusion is supported by our contextual analysis. Three community variables — percent black, percent poor, and population size — constitute a powerful explanation for individual and group variations in exposure to crime. Once they are entered into the models, few individual-level predictors remain significant. Equally important, most of the group differences disappear. In the case of blacks, one can conclude that, whatever their individual characteristics of income, homeownership, etc., they are more exposed to crime mostly because they tend to be channeled into larger suburbs with relatively high black and poor proportions; in the case of Asians, because they are located in larger suburbs. The finding for blacks points up the continuing significance of segregation (Alba & Logan 1993; Massey & Denton 1988). In this respect, the place-stratification model receives support from our analysis, for it predicts that a hierarchy of places is used to preserve social distances among groups and that members of disadvantaged groups, even when their other personal characteristics are favorable, tend to be channeled into communities of disadvantage. Surely, high community crime rates constitute such a disadvantage, even for those individuals who are not directly victimized by crime.

APPENDIX A: Estimating Models of Locational Attainment

Our purpose here is to explain in somewhat more detail the method that we use to estimate OLS regressions models of locational attainment from UCR and census data (a more complete explanation can be found in Alba and Logan 1992). As the text states, the essential principle in our strategy is to construct a correlation (or covariance) matrix from different sources: rows and columns that pertain to aggregate variables are estimated from tabulated data (taken from the UCR file and Summary Tape Files 3 and 4); the remaining elements, which pertain to individual-level variables only, come from the Public Use Microdata Samples (PUMS) data.

To estimate the correlations for aggregate variables, whether these correlations are with individual-level variables or other aggregate ones, we first assemble a data file for communities. It contains, for each community, the values of the aggregate variables, along with tables of individual-level characteristics. Appendix B presents a small section extracted from the file used as the basis of the regression models for non-Hispanic whites in Tables 4 and 6. The crime rate shown is derived from the UCR data (and census population totals), and the natural logarithm of population size is calculated from Summary Tape File 3. The communities in question are New Jersey suburban towns (or "minor civil divisions," in census terminology); only 10 of the 217 in the non-Hispanic white file are shown here. The individual-level characteristics — homeownership and nativity/period of immigration are shown here — are represented as counts for non-Hispanic whites and come from Summary Tape File 4B. Note should be taken of an implied principle: Noncensus variables, such as crime rates, can be included in such a file and hence incorporated in locational-attainment models whenever these variables characterize some unit of census geography for which the required individual-level tables are also available.

Consider now the problem of estimating the correlation for non-Hispanic whites between the violent crime rate (Y) and a dummy variable (X_3) representing recent immigration (i.e., immigration since 1974). We assume that the violent crime rate can be considered to be the same for all residents of the same community (thus the method obliges us to regard the crime rate as a community characteristic and to ignore within-community variations). Then, the components of the correlation in the standard computing formula (see Blalock 1979:400) — $\sum X_3Y$, $\sum X_3^2$, $\sum Y^2$, $\sum X_3$, $\sum Y$ and N — can be calculated directly from the file excerpted in Appendix B. For every recent immigrant in a community, $X_3 = 1$, and Y is the value of the violent crime rate; for everyone who is not a recent immigrant, $X_3 = 0$, and Y is the same as before. The contributions to the components of the correlation are calculated accordingly. For instance, for the town of Demarest, the contribution to the $\sum X_3Y$ component is 11,304, because there are 33 recent immigrants and the crime rate is 342.54 (those who are not recent immigrants do not contribute here because X_3 is 0 for them); the $\sum X_3^2$ component goes up by 33, due solely to the count for recent immigrants; the $\sum Y^2$ component is increased by 5288.2×10^5, because the value of Y^2 is the same for every resident (1.17334×10^5), and the count of non-Hispanic white residents is 4,507; and so on. These contributions to the components are added across all communities in the file, and the correlation is calculated. In this case, it is .029.

There is a new wrinkle introduced by the calculation of the correlation between the violent crime rate and individual homeownership. In this case, the census table for individuals omits individuals who do not reside in households. Thus, to calculate the correct correlation, the count for nonhomeowners in each community must be augmented by that for individuals who reside in what the Census Bureau labels as "group quarters" (shown as X_6). Moreover, to interpret correctly the coefficient of the homeownership dummy variable in the regression model, a variable for group-quarters residence must be included; otherwise, the homeownership variable will be compared inappropriately to an omitted category that contains both renters and those in group quarters. The group-quarters dummy variable is, in fact, relevant for

APPENDIX A: Estimating Models of Locational Attainment (Continued)

other variables that characterize households and appears in the tables under the heading "Household Structure." Apart from this consideration, the calculation of the correlation between crime and homeownership is the same as before: the result is -.186. Finally, for the contextual analyses, we need to calculate the correlation at the individual level between the property crime rate and the logarithm of community population size. This is just a weighted correlation, where the weight in this case is the number of non-Hispanic white residents. These considerations close out the calculations for the row and column of the correlation matrix pertaining to the violent crime rate. Exactly analogous procedures can be used to calculate any correlations for logged community population size. To complete the matrix, we must calculate the correlations among the individual-level variables (e.g., homeownership with recent immigration). These correlations cannot be calculated from an aggregate data file, and so we must turn to the PUMS data (5% sample). To do these calculations in a manner consistent with those above, three requirements must be met:

(1) Cases must be counted in the same way. In the aggregate files, such as that shown in part as Appendix B, our tables of individual-level characteristics include all individuals who belong to a given racial/ethnic population, regardless of position within a household. This is required because some of our variables of interest, such as nativity/period of immigration, are reported only in this way. In extracting cases from the PUMS file for the calculation of correlations, we must select cases in the same way. We cannot, for example, restrict PUMS calculations to householders, if other correlations include all household members.

(2) Variables must be defined consistently. Since we have defined dummy variables at the individual level to correspond with the counts reported in Appendix B, we must do the same in defining variables in the PUMS data. Some care must be exercised to guarantee consistency. For instance, the homeownership count in Appendix B is the count of individuals who live in an owner-occupied household. The homeownership variable defined in the PUMS must have the same meaning.

(3) The geographic boundaries covered by the aggregate and PUMS files should correspond. This is the one principle where compromise is sometimes forced, as is true here. The geography targeted by our analysis is the suburban New Jersey portion of the New York City CMSA. In the aggregate files, we fall short of covering this geographic region because the crime rates are not known for some smaller towns and also because tables are not reported (they are "suppressed") by the Census Bureau when the size of a racial/ethnic population in a town is below a certain threshold (30). Even so, the great majority of individuals in all groups who reside in the region of interest is covered in our aggregate files, as the text points out. In the PUMS extracts, we cover slightly more than the intended region, because some small central cities, such as Sayreville, are not identifiable and thus their residents cannot be separated from the suburban population. In any event, we approximate the region of interest in both files.

Assuming that these requirements can be met, there is great consistency between correlations calculated from the PUMS and those from census aggregate files, because both are derived the same source, the sample of Americans who completed the long form of the 1980 census. Only the crime rate variables have a different source here. Once the correlations have been calculated in these different ways, they are assembled into a single matrix, such as the truncated one presented in Appendix C. The matrix is augmented by vectors of means and standard deviations calculated at the individual level from the aggregate files (which have larger *Ns* and thus yield more precise estimates). *Ns* are supplied based on the numbers of cases for each racial/ethnic population in the PUMS data (and are fixed at 10,000 if the number of cases is larger). The resulting matrix and vectors are fed into a standard regression package (such as SPSS-X) to calculate the regression models we report.

APPENDIX B: Excerpt from Aggregated File Used to Calculate Correlations Pertaining to Aggregate Variables[a]

	Violence Rate	Native-born	Arrived before 1975	Arrived after 1974	Home-owner	Home Renter	Group Quart.	Ln Pop. Size
	Y	X_1	X_2	X_3	X_4	X_5	X_6	X_7
Allendale Borough	508.39	5,345	352	83	5,131	463	186	8.68
Bergenfield Borough	516.27	20,655	2,209	173	18,874	4,163	0	10.15
Demarest Borough	342.54	3,988	486	33	4,341	135	31	8.51
Elmwood Park Borough	740.06	15,176	1,894	108	12,050	5,128	0	9.82
Hasbrouck Heights Borough	484.96	10,735	907	16	9,382	2,276	0	9.41
Lodi Borough	1,114.54	19,290	2,549	251	11,801	10,147	142	10.08
Norwood Borough	521.19	3,735	419	23	3,931	246	0	8.39
Ridgefield Park Village	667.29	10,788	1,092	51	7,960	3,936	35	9.45
Teaneck Township	843.44	23,575	2,814	423	21,719	3,938	1,155	10.57
Wood-Ridge Borough	945.89	7,101	541	28	6,454	1,216	0	8.98

[a] Non-Hispanic white models

Notes

1. By the greater New York City metropolitan region, we mean the large region described by the Census Bureau as the New York-Northern New Jersey-Long Island Consolidated Metropolitan Statistical Area (CMSA). This metropolitan region includes 12 Primary Metropolitan Statistical Areas (PMSAs) and spreads across parts of three states — Connecticut, New Jersey, and New York. We restrict ourselves to the New Jersey portion for data reasons that we make clear in a later section.

2. Data having this format are also unusual in victimization surveys. Smith and Jarjoura (1989) note the bifurcation in the victimization literature between individual-level and aggregate-level studies, which parallels the division within research on residential location. Nevertheless, even were cross-level data more available in victimization studies, these would not substitute for the kind of study we carry out here. Studying the risk of crime at an individual level cannot directly inform us about locational outcomes, because the individual-level effects in such a study potentially confound effects on residential location, which we study here, with the effects on risk among residents of the same places, which we do not study. Victimization research, by contrast, aims to study the latter rather than the former (see Cohen & Felson 1979; Smith & Jarjoura 1989).

3. Of course, these distributions must all be based on the same unit, and this requirement can necessitate a thorough search of census tabulations. For our analysis, we have selected tables (distributions) for individuals (rather than, say, households), in part because these tables offer

APPENDIX C: Portion of Correlation Matrix with Means and Standard Deviations[a]

	Y	X_1	X_2	X_3	X_4	X_5	X_6	X_7	Mean	Std. Dev.
Y Violence rate	1								871.840	599.450
X_1 Native born	-.048	1							.911	.284
X_2 Before 1975	.042	-.955	1						.082	.274
X_3 After 1974	.029	-.272	-.024	1					.007	.084
X_4 Home owner	-.186	.036	-.019	-.062	1				.758	.428
X_5 Home renter	.181	-.031	.013	.062	-.956	1			.228	.420
X_6 Group quarters	.032	-.021	.021	.002	-.228	-.069	1		.014	.117
X_7 Ln pop. size 3A	.258	-.042	.018	.018	-.108	.103	.025	1	9.981	.816

[a] Non-Hispanic white models

the widest range of characteristics. In only one case, that of household income, did we have to resort to a tabulation for households. But the table we selected presents income categories by size of household and is thus readily converted to a table whose counts represent individuals. Partially missing data, or the coverage of tables, give rise to another issue. Many census tabulations do not cover all residents of a place — for example, household income and homeownership tabulations include only individuals residing in households, ignoring those in institutions; language tabulations include only persons 5 and older. To be usable in our analysis, these and similar tables must be completed by adding appropriate categories to contain the remaining cases. This, in turn, generates a novel feature in our variable construction: variables that share the same category. For instance, several variables contain a group-quarters category (which, to be sure, represents the same population in each case). Interpretation of the effects of these shared categories must reflect their involvement in several variables (for further discussion, see Alba & Logan 1992).

4. Since metropolitan regions and the geography of the PUMS data are both defined in terms of counties, it is not hard to make the metropolitan boundaries coincide in the two data sources. A small divergence arises, however, because our study is focused on suburbs and thus requires us to exclude central-city residents. This is easily done in data from the Summary Tape Files, but several small central cities (such as Sayreville, New Jersey, with a population under 30,000 in 1980) are not identifiable in the PUMS data we are using (a geography). Their residents are therefore included in our PUMS calculations.

5. This was confirmed by a logistic regression analysis of appearance in the UCR data. With a variety of community characteristics — including racial composition, percentage foreign born, median household income, and age distribution — in the equation, population size was by far the strongest predictor of a community's presence in the UCR data.

6. In fact, the correlations from the PUMS are based on as many cases as were available, but we have fixed the *N* at 10,000 in estimating regression results. Only for Asians is the number of cases in the PUMS data smaller than 10,000. For the Asian analysis the degrees of freedom are based on 3,625 cases.

7. For those accustomed to the high R^2 values common in ecological (i.e., aggregate-level) analyses, the values in Table 2 may look modest. However, it must be kept in mind that all communities are internally heterogeneous in terms of the independent variables, and this constrains their ability to explain a community characteristic.

8. The formula for the standard test for coefficient differences across equations is:

$$t = (b_1 - b_2) / \sqrt{(s.e._1^2 + s.e._2^2)}$$

where s.e.$_1$ and s.e.$_2$ are the standard errors of the regression coefficients (shown in Tables 3 and 4). For example, the t value by this formula for the difference between the black and white coefficients for the top income category in Table 4 (592 and 269, respectively) is 2.20, which is significant at the .05 level.

9. The Asian homeownership coefficient is significantly different from the black and Hispanic coefficients, but not from that for whites.

10. The equations for blacks show one oddity with respect to community size: it has apparently negative effects on exposure to crime. This reversal of expected sign appears to be due to multicollinearity among the three contextual variables, which is severe only in the black case.

11. For the population size variable, one unit of increase represents a 2.7-fold increase in actual population because of the logarithmic scale employed. For the other two variables, one unit represents one percentage point — clearly, a different order of magnitude of increase. In standardized terms, the coefficients of logged population size in the property crime equation go from -.046 (among blacks) to .222 (among Hispanics), while those for racial composition go from .316 (among whites) to .609 (among blacks). The contrast makes evident the different levels of explanatory power of the two variables.

12. The average black suburbanite in this region resides in community that is 39.6% black, 12.1% poor, and has a logged population size of 10.64 (equivalent to a population of 41,800). By comparison, the average New Jersey suburb is 3.5% black, 5.4% poor, and has a logged population size of 8.89 (equivalent to a population of 7,300).

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