WESTERN CRIMINOLOGY REVIEW

Western Criminology Review 7(3), 7–26 (2006)

The Distribution of Property Crime and Police Arrest Rates across Los Angeles Neighborhoods

John B. Davis
ERS Group

Abstract. *A cross section of 636 Los Angeles neighborhoods in 1987 is used to examine relationships between neighborhood rates of property crime, levels of policing as measured by neighborhood arrest rates, jobs per square mile, and characteristics of neighborhood residents. Endogeneity between neighborhood crime and arrest rates is explored by estimating a regression model with and without control variables for neighborhood characteristics and fixed area effects. When comparing nearby neighborhoods with similar characteristics, crime is lower where arrest rates are higher, but when comparing neighborhoods across the city without controls, arrest rates are higher in higher crime, lower income minority areas.*

Keywords: property crime; geography of crime; arrest rates; jobs; aggregate crime statistics

Introduction

Economic theories of crime posit that, all else equal, criminals are more likely to engage in criminal activity when and where the expected gains are higher, with the risk of arrest by the police as a key factor affecting the expected gains to criminal activity (Becker, 1968; Phillips and Votey, 1972). There is general agreement in the literature on how the economic model guides expectations about criminal behavior, but there is a wide range of debate about the extent of empirical support for the economic approach due to problems in accurately identifying and measuring these relationships, especially in studies that use aggregate data on crime rates and explanatory characteristics (e.g., at the city-wide, county, or state level). One common problem is difficulty in measuring variables that affect criminal behavior, since the typical candidates are proxy measures that do not distinguish criminal opportunities from criminal motives or are simply omitted entirely. The most difficult statistical issue, however, stems from the simultaneous determination of crime with variables that explain crime rates, such as police arrest rates and criminal opportunities, all of which may change as the public responds to rising crime.

This paper explores these issues using a more localized unit of observation than many previous studies of aggregate crime statistics: 636 neighborhoods (essentially census tracts) that comprise Los Angeles (L.A.) in 1987. The data set contains information to separately identify and control for key factors that should affect property crime, factors often omitted in other studies. In an effort to identify simultaneous influences on property crime from property crime arrest rates, the statistical model is estimated with and without control variables and with and without controls for city areas. As will be discussed, there is a positive relationship between property crime and arrest rates when estimated across neighborhoods of the city when control variables and area effects are excluded from the model, but a negative relationship when estimated with controls for neighborhood characteristics and area effects that restrict measured relationships to variation between similar neighborhoods within city areas.

Economic Model of Property Crime

The economic model of crime is especially relevant for modeling property crime as compared to violent crime due to its clear economic motives. The economic model of property crime posits that property criminals increase or decrease criminal activity in response to changes in their motivations for criminal activity, M_n, the benefits or loot that can be acquired from criminal activity, $B_n(C_n)$, and the risks of arrest and punishment for criminal activity, $a_n(C\text{n})$, which together increase or decrease the net returns (NR_n) to criminal activity in a neighborhood, n:

$$NR_n = f\,[\,\underset{+}{M_n},\ \underset{+}{B_n(C_n)},\ \underset{-}{a_n(C_n)}\,] \qquad (1)$$

In the context of a city with alternative neighborhoods for committing property crime, property criminals can be modeled as assigning an optimal probability for selecting

each neighborhood, c_n^*, in their area of N neighborhoods of criminal activity in order to maximize the net return from their criminal activity[1]:

$$c_n^* = NR_n / (\Sigma_n^N NR_n)$$

$$\text{where } c_n \geq 0 \text{ and } \Sigma_n^N c_n = 1 \text{ and } n = 1, \ldots, N \qquad (2)$$

In other words, criminals are described as routinely visiting each neighborhood n in their area of N neighborhoods at a rate of "c_n^*" percent of the time based on their assessment of the different net returns to property crime in each of the neighborhoods in the area with which they are familiar. Thus, neighborhoods that criminals perceive to have higher net returns are visited proportionally more often than neighborhoods with lower net returns, resulting in more property crimes being committed in these neighborhoods. Each neighborhood's rate of property crime, C_n, is then essentially driven by variation in the factors that affect the net returns to crime between neighborhoods and should therefore attract criminals to a neighborhood.

The theoretical model can be specified with a generalized logarithmic regression equation for statistical estimation[2]:

$$log\,(C_n) = \beta_M\, log(M_n) + \beta_B\, log(B_n) + \beta_a\, log(a_n) + \alpha_{PRA}\, PRA_{Area} + \varepsilon_n$$

$$\text{where } \varepsilon_n \sim N(0, \sigma_n^2) \qquad (3)$$

Subscript n denotes the neighborhood unit of observation and the subscript *Area* on the *PRA* variable denotes areas containing multiple neighborhoods. Since dependent and independent variables in such an equation are logged, the coefficients estimated by the equation represent the percentage change in property crime between neighborhoods that is associated with a one percent change in the factors that affect property crime in different neighborhoods. Notably, a selection probability model of this sort allows for dual equilibrium in which neighborhoods with low property crime can coexist with neighborhoods with higher property crime[3].

In order to apply a model of criminal supply decisions where criminals weigh the net returns to crime between neighborhoods within limited areas of the city to the entire city, fixed intercept terms, PRA_{Area}, are included in the equation that identify areas containing a number of nearby neighborhoods among which criminals are likely to be able to exhibit some mobility. Fixed area effects can account for systematic differences in crime rates between areas due to different populations of criminals and average crime opportunities in these areas[4], as well as provide a crude control for spatial autocorrelation between nearby neighborhoods[5]. The grouping of neighborhoods into fixed effect areas is based on the boundaries of eighteen different Los Angeles Police Department (LAPD) Police Reporting Areas (*PRA*s). Grouping neighborhoods by *PRA* is somewhat arbitrary with respect to areas that criminals may consider within their range of neighborhoods for criminal activity. However, grouping neighborhoods by *PRA* has the advantage of corresponding with the LAPD command-and-control structure that oversees the allocation of police between neighborhoods within these areas. Fixed area effects defined in this way can account for systematic differences in policing strategies for neighborhoods in different *PRA*s, which is one factor that affects criminals' assessment of the net returns to property crime.

The fixed effects technique is typically used in longitudinal data analysis to account for systematic and unobserved differences between individual units of observation that are followed over time. To the author's knowledge, this technique has not been used to analyze purely cross-sectional crime data. However, similar to the strategy in this paper, Dugan, Nagin, and Rosenfeld (2003) use larger area fixed effects than the unit of observation in a longitudinal context (e.g., state fixed effects for multiple observations of cities within states over time) as a means of economizing on the amount of variation used up by a complete set of fixed effects. Dugan et al. (2003) even drop all fixed effect variables for some panels of their data when doing so has a negligible impact on the estimates. Dropping all fixed effects for *PRA*s from the model estimated in this paper, in contrast, substantially alters the estimates of the relationship between property crime rates and property crime arrest rates, indicating that area controls are important.

The statistical model of neighborhood property crime rates is based on the model of criminal supply responses to the key factors that affect the net returns to crime. However, some of these factors, such as arrest rates and criminal opportunities, are likely to respond simultaneously with changes in the neighborhood crime rate. Thus, the estimates from the model can only be interpreted as *net* effects that mix criminal supply responses to changes in explanatory factors with simultaneous responses of these factors to differences in property crime rates between neighborhoods. To explore the direction of the simultaneous influences that may confound the interpretation of estimated relationships, the model is estimated at different levels of aggregation, with and without control variables, and with and without fixed area effects. The expected directions of simultaneous influences on estimated relationships are discussed in detail below.

Measurement of Motives and Opportunities to Commit Property Crime

Aggregate variables used in many studies, such as unemployment rates, commonly fail to separately identify motives versus opportunities for crime commission. Kleck and Chiricos (2002) note that studies that find a positive relationship between crime and the unemployment rate interpret the unemployment rate as a proxy for increased motivations to commit crime, since it may reflect reduced lawful earnings opportunities for criminals. On the other hand, they note that studies that find a negative relationship between crime and unemployment rates interpret the unemployment rate as a proxy for reduced opportunities to commit crime as the unemployed population more carefully guards their property. These ad hoc interpretations of results highlight the problem of failing to separately identify the motives versus opportunities to commit property crime. Kleck and Chiricos (2002) attempt to address this problem using a data set for Florida counties with separate measures for criminal motivations (resident poverty rates) and criminal opportunities (e.g., the number and value of sales at retail establishments). Along similar lines, this paper attempts to distinguish criminal motives from criminal opportunities by using different proxy variables for each.

The average household income of neighborhood residents is used to reflect motivations to commit property crime, M_n, in a particular neighborhood n. The literature commonly associates the high crime found in some city neighborhoods with the characteristics of neighborhood residents including poverty, disintegrated family structure, unemployment, and the compounding of these social ills for residents in these neighborhoods (Comanor and Philips, 1995; Ludwig, Duncan, and Hirschfield, 2001; Ralston, 1999; Wilson, 1987). Research has also indicated that property criminals, especially when using property crime to finance drug use, tend to commit crime near where they live and in neighborhoods with which they are familiar (Wright and Decker, 1994). Thus, lower average household income for residents of a neighborhood may correlate with higher neighborhood crime to the extent that mobility costs for criminals lead local criminals to prefer committing crime nearer to home.

Opportunities to commit property crime in a neighborhood, $B_n(C_n)$, are distinguished from motives to commit property crime in a neighborhood by using a proxy that has some variation distinct from the characteristics of neighborhood residents, in particular, jobs per square mile for people working but not necessarily living in the neighborhood. Business versus residential zoning, the different market forces affecting residential versus business activity, and the fact that workers are not identical to the residents of a neighborhood should enable jobs per square mile to exhibit some independence from the residential characteristics of each neighborhood and thereby provide a measure of crime opportunities that is independent of criminal motives. As noted above, Kleck and Chiricos (2002) have attempted to measure criminal opportunities by economic activity at business establishments, although they did not find significant relationships. Jobs may be a better proxy for criminal opportunities, since workers are more readily observable than levels of economic activity such as total sales[6].

Measures of economic activity in a neighborhood are not, however, expected to be independent of neighborhood property crime rates. In particular, potential victims may respond to rising crime by avoiding activity in more dangerous neighborhoods in preference for safer neighborhoods (i.e., $\partial B_n(C_n)/\partial C_n < 0$). This can lead to a negative correlation between crime and jobs that counters the positive correlation expected from the attraction of crime to jobs. If a net positive relationship is found between crime and jobs, then the simultaneous response of jobs to crime is a smaller effect than the attraction of crime to jobs. On the other hand, if a negative relationship is found then it is not clear that the measure succeeded in reflecting criminal opportunities.

Aggregate variables proxy for criminal opportunities and motivations indirectly and, as a result, are unlikely to completely capture all the relevant factors affecting crime for a particular neighborhood. One way to account for this data limitation is to employ fixed effects to capture unobservable differences in criminal motives and opportunities in each unit of observation. For example, Marvell and Moody (1996) include fixed effects for each unit of observation in a time-series cross section analysis of aggregate city and state data. The data analyzed in this paper are from a single cross section of neighborhoods in L.A. in 1987 that contains no time series observations so that a fixed effect for each neighborhood cannot be used. As an alternative, eighteen fixed area effects are used that identify groups of about 35 nearby neighborhoods and correspond to Police Reporting Areas (*PRA*s) of L.A.

Measurement of the Risk of Arrest

The arrest rate or ratio of the total number of arrests compared to the total number of crimes in a locality, ($a_n = A_n/C_n$), is a commonly used measure for the risk of punishment for committing a crime. The LAPD in 1997 reports data that show that arrest rates correspond with higher

dollar costs of police per square mile and per resident, indicating that it is reasonable to use arrest rates as a measure of police efforts (LAPD, 2005). A higher arrest rate is expected to reduce criminal activity through deterrence or incapacitation of criminals (Levitt, 1998b). Studies in a neighborhood context have found that increased policing reduces or displaces crime from a neighborhood (Kelling and Pate, 1974; Press, 1971). Similarly, analyses based on city and county level data, have found that independent increases in the level of police manpower reduce crime (Kovandzic and Sloan, 2002; Marvell and Moody, 1996; Levitt, 1997). In a neighborhood cross section, the economic model of crime would interpret a negative relationship between the arrest rate and the crime rate as deterrence, displacement, or incapacitation of criminals in a neighborhood. However, measuring an independent effect of the arrest rate on the crime rate is difficult since the arrest rate is not independent of the crime rate. Further complicating interpretation, different strains of the literature predict different responses of the arrest rate to the crime rate.

Negative Simultaneity between Property Crime and the Arrest Rate

One strain of the criminology literature argues that arrest rates (as the ratio of arrests to crimes) should simultaneously *decline* with higher crime rates (Ehrlich, 1973; Glaser and Sacerdote, 1999). This literature has used cross sectional data sets with observations on separate cities or U.S. states between which there is little chance of redistributing police resources, such that the implicit assumption is that police resources are fixed within a unit of observation. When the number of police assigned to patrol a locality is fixed, then the total number of arrests that can be made in the locality will also be limited. In such a situation, the rate of arrest faced by each criminal in the locality will shrink towards zero as criminal activity rises and, at the extreme, overwhelms the fixed number of police patrolling the location, ($\partial a_n(C_n)/\partial C_n < 0$ and $\partial^2 a_n(C_n)/\partial^2 C_n > 0$ when A_n is fixed). Los Angeles' 1965 Watts riot and the 1992 riot in South Central provide good examples of how the risk of arrest can shrink to zero as the police are overwhelmed by a sudden rise in criminal activity. At the intersection of Florence and Normandie where the 1992 riots began, there were about 35 officers facing a growing mob of at least 200 before the officers fled the scene (Cannon, 1999). Fiscal limitations and other policing demands, such as traffic control, may also make it difficult for the police to maintain arrest rates in neighborhoods with particularly high crime rates over the long term. Indeed, the LAPD had no expansion of its police force in the 8 years prior to 1987 (Cannon, 1999)[7]. Despite these constraints on police responsiveness to changes in crime rates, assuming that the police are unable to respond to increases in crime for particular neighborhoods is at odds with the standard police practice of responding to reports of crime as quickly and effectively as possible.

Positive Simultaneity between Property Crime and the Arrest Rate

Another strain of the literature suggests that there can be a *positive* response of arrest rates to crime rates. This literature, also using aggregate data sets but including observations across time, has found that police manpower levels increase with rising crime rates. This has generally been interpreted as a public response to rising crime in which the public chooses to increase police resources, financing, and manpower through the electoral and/or budget cycle to combat rising crime (Kovandzic and Sloan, 2002; Marvell and Moody, 1996; Levitt, 1997)[8].

For a cross section of neighborhoods in a city, a police response that increases neighborhood arrest rates in response to higher crime may occur as a matter of practice well before a new budget cycle. In the late 1980s, the LAPD could be distinguished from precinct based police departments in east coast cities by a more centralized militaristic administrative structure, a centralized research division, and a high degree of autonomy from the city political structure (Cannon, 1999; Alonso, 2005). This centralized administrative structure enabled strategies that could allocate resources between neighborhoods and across the city in response to differences in crime rates. Resources could be allocated to higher crime areas based on longer term information, such as the monthly records from which the data set in this paper is gathered, or more strategically based on assessments of historical trends. For example, in 1988 a contingent of about 1,000 officers was used to sweep through South Central neighborhoods and clear out crime, drugs, and gangs in "Operation Hammer" (Cannon, 1999). A police response to rising crime in a particular neighborhood can also occur instantaneously based on technologies for the reporting of crime (e.g., via 911). Similarly, the advent of Mobile Digital Technology (MDT) in 1983 allowed "e-mail" type communication between patrol cars (Cannon, 1999) and, according to the LAPD, "greatly accelerated response to citizen calls for service via computers installed in black and white patrol vehicles" (LAPD, 2006).

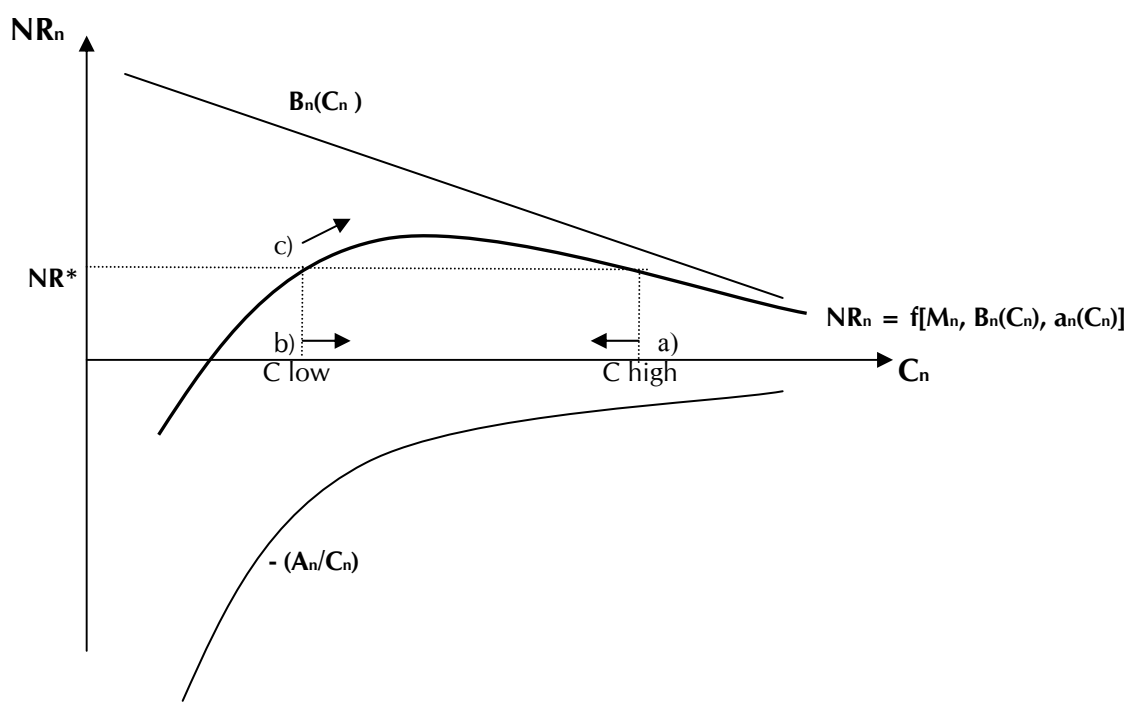
The LAPD collects detailed arrest statistics by date, location, and type of crime, which creates the capacity for arrest rates to be used as an administrative measure of

police effectiveness. The Christopher Commission that reviewed the LAPD's use of force after the Rodney King beating noted that the LAPD made arrests a requirement for promotion and pay advancement (Cannon, 1999). A more general statement of the theory that the arrest rate may represent the public response to crime should also consider other factors that may affect arrest rates, such as the tactics of crime control (e.g., community policing) and the types of force that officers are allowed to use in arresting a suspect (e.g., choke holds or batons). Arrest rates are also likely to be related to neighborhood characteristics. For example, it may be that arrests for additional crimes are easier in higher crime areas, because the typical suspect arrested in one crime may be implicated in other crimes and implicate others leading to additional arrests. Another possibility is that the police are more inclined to make arrests in lower income minority neighborhoods where the typical suspect has less recourse to legal defense. Such a perception certainly existed in the African-American community of L.A. since the late 1960s when groups such as the Black Panthers organized to "police the police" (Alonso, 2005) and was reinforced in the 1980s by police activity, such as the raid on an apartment complex at 39th and Dalton based on a false tip in which dozens of officers were subsequently disciplined for bad conduct (Cannon, 1999).

Separation of Neighborhoods into High and Low Property Crime Areas

Figure 1 describes the net returns to property crime for two nearby neighborhoods with equivalent crime opportunities and police protection, but different levels of criminal activity, (C low and C high). The expected arrest and punishment curve, $-(A_n/C_n)$, approaches zero as

Figure 1. Net Return to Crime as a Function of the Neighborhood Crime Rate



Legend

C_n Crime rate of the **n**th neighborhood, (x-axis). "C low" marks the crime rate in low crime neighborhood, "C high" marks the crime rate in high crime neighborhood.

$NR_n = f[M_n, B_n(C_n), a_n(C_n)]$ – Net return to crime in the **n**th neighborhood (mapped as a function of the crime rate by bold curve with resulting level of net returns on y-axis).

$B_n(C_n)$ Crime opportunities in the **n**th neighborhood as a function of the crime rate, **C_n**.

$a_n(C_n) = (A_n/C_n)$ – Costs associated with risk of arrest and punishment as a function of the number of arrests, **A_n**, and crime rate, **C_n**.

M_n Motivations to commit crime in the **n**th neighborhood.

NR* Level of equivalent net return to crime in two neighborhoods of the city.

crime rises, which shows the negative simultaneity that occurs as a fixed number of police are overwhelmed by rising crime. Opportunities for committing crime, $B_n(C_n)$, decline more steadily as crime rises, which shows the negative simultaneity that occurs as the best targets are eliminated or flee as crime rises. Together, these variables map the net returns to crime at different crime rates, NR_n (see bold curve in Figure 1).

In this scenario where the two nearby neighborhoods have equivalent fixed police resources, a criminal at the margin in the high crime neighborhood has an incentive to a) reduce crime activity in the high crime neighborhood, b) switch criminal activity to the low crime neighborhood even with equivalent net returns to crime, because c) the lower crime neighborhood will offer a higher net return to crime upon the arrival of the criminal (see Figure 1). This results because the rate of arrest and punishment in the low crime neighborhood drops rapidly with the arrival of criminals from other neighborhoods (note the relatively steep slope of the expected punishment curve at lower crime rates as compared to higher crime rates in Figure 1), while the total stock of crime opportunities declines more steadily as opportunities are targeted by additional criminal activity. As a result, the net return to crime for the marginal criminal in a lower crime neighborhood may actually increase with the arrival of criminals to the neighborhood, because the decline in the arrest rate is greater than the decline in crime opportunities. On the other hand, criminals from lower crime neighborhoods will have no incentive to visit higher crime neighborhoods with equivalent net returns to crime at the margin, because net returns fall with the arrival of additional criminals to higher crime neighborhoods. Indeed, criminals in higher crime neighborhoods have an incentive to keep visiting criminals away, which offers a potential explanation for gang territories (see related arguments in Fiorentini and Peltzman, 1995).

If the assumption of fixed police resources in each neighborhood is relaxed, then the police can shift resources between neighborhoods. If the police move resources from the low to the high crime neighborhood (enabling more total arrests in the high crime neighborhood and flattening the expected arrest and punishment curve), then there are even more incentives for criminals to shift activity to the low crime neighborhood. If the police move resources from the high to the low crime neighborhood (enabling more total arrests in the low crime neighborhood and inclining the expected arrest and punishment curve), then criminals have fewer incentives to shift activity to the low crime neighborhood, but also fewer risks to criminal activity in the high crime neighborhood. On the other hand, when the two neighborhoods are geographically distant, then switching criminal activity between the neighborhoods becomes more costly and less likely. This creates an opportunity for the police to shift resources from the low to the high crime neighborhood without inviting criminals to simply switch activity to the low crime neighborhood. Such a strategy has the potential for reducing crime in the city overall if increases in crime in the low crime neighborhood are small when police resources are extracted. Such a strategy can also generate a positive relationship between arrest rates and crime when measured between greater geographic distances.

Data for Los Angeles Neighborhoods in 1987

Neighborhood crime rate equations are estimated separately for the felony crimes of robbery, burglary, auto theft, felony theft, and for these crimes aggregated together based on annual totals for crime and arrests for 636 neighborhoods that comprise L.A. in 1987[9]. The Federal Bureau of Investigation and many researchers classify robbery as a violent crime rather than a property crime due to the threat of violence, although the motive for obtaining items of value is noted (Federal Bureau of Investigation, 1990). Even burglary involves a chance of violence when home dwellers surprise a burglary in progress. Thus, these crimes may be classified on a scale from less to more serious by the potential for violence they entail. Robbery is included along with property crimes in the equations for aggregate property crime estimated in this paper, since robbery involves the motive of acquiring property that is the basis of the economic decision model in this paper. Another reason to include robbery in the aggregate property crime rate is that arrest efforts for different neighborhoods and areas of L.A. are likely to be especially influenced by more serious crimes, such as robbery.

Neighborhoods are defined by the boundaries of 636 Police Reporting Districts, which are subunits of the Police Reporting Areas (*PRA*s) used to identify fixed area effects. Police Reporting Districts correspond with U.S. census tracts and average 0.75 square miles in size (a handful of census tracts were aggregated together to match the larger Police Reporting Districts). Annual crime and arrest data for each neighborhood in 1987 is obtained by summing the crime and arrest totals from monthly reports for each Police Reporting District in L.A. across the year. These data are compiled by the LAPD and are publicly available in non-electronic form at the L.A. Municipal Library (LAPD, 1987). Crime and arrest data are matched by census tract to demographic information on neighborhood residents from the 1990

U.S. Census, to counts of jobs per neighborhood from the California Department of Employment in 1986, and to indicators of neighborhood features based on historical maps[10].

In order to compare the number of crimes committed in neighborhoods of different size, the rate of crime in each neighborhood, C_n, is defined as the annual number of crimes reported in the neighborhood in 1987 divided by the number of square miles the neighborhood spans. The literature, in contrast, typically defines the crime rate as the total number of reported crimes divided by the resident population for larger geographic areas than neighborhoods within a city, such as entire cities, counties, or states (Levitt, 1997, 1998b; Kleck and Chiricos, 2002). This is insufficient for neighborhoods within a city, because workers, customers, and travelers visiting a neighborhood may be victims of crime in addition to residents of the neighborhood.

The average annual household income of neighborhood residents in 1989 from the 1990 U.S. Census is included in the model to proxy for motivations to commit crime in a neighborhood, M_n. Other variables such as residential density (residents per square mile) and the percent of neighborhood residents that are African-American or Hispanic may also capture motivations to commit crime by reflecting omitted characteristics such as poverty (see Table 1 for a complete list of variables included in the model).

Like the crime rate, the measure of crime opportunities is defined as a rate per square mile. The number of jobs in each neighborhood, tallied by the California Department of Employment in 1986, divided by the square miles of each neighborhood is used to proxy for the stock of crime opportunities in a neighborhood, $B_n(C_n)$. In addition, indicator variables for the presence of a local or regional shopping center or a downtown location are included in the model and may also proxy for crime opportunities in a neighborhood. These variables may identify a greater number of property crime opportunities in a neighborhood by reflecting greater economic activity and their attendant numbers of customers, workers, and merchandise that may be crime targets. Criminals' preferences over the number of jobs per square mile in a neighborhood should correspond in direction to criminals' preferences over the marginal value of property crime opportunities in a neighborhood to the extent that greater economic activity makes more valuable property available for theft in a neighborhood and that criminals first target the most lucrative crime opportunities.

Since employment totals are measured in 1986, while crime is measured in 1987, simultaneity between crime and jobs per square mile may not be pronounced in this data set, since current variations in crime can only affect lagged employment through forward looking behavior on the part of workers and employers in the neighborhood. Similarly, simultaneity between the current crime rate and other measures of economic activity, such as the presence of a shopping mall in a neighborhood, is limited since the construction and leasing decisions for the creation of malls occur at earlier points in time. Jobs per square mile, on the other hand, involves individual decisions about changing jobs with relatively lower sunk costs in many cases, so this variable still has some potential to exhibit simultaneity with variations in the crime rate.

For each type of crime, the risk of arrest faced by criminals active in each neighborhood, a_n, is measured by the annual number of arrests divided by the annual number of crimes reported in each neighborhood. In actuality, criminals may gauge their chances of being caught in loosely defined areas based on personal experience of being stopped by police in the neighborhood, visible street presence of police in the neighborhood, or word-of-mouth about neighborhoods where other criminals have been arrested. Thus, neighborhood arrest rates only proxy for the chances of arrest in a neighborhood as perceived by criminals who are considering criminal activity in a particular neighborhood. Indeed, robbery arrest rates exceed 100 percent in 17 neighborhoods suggesting that criminals either get arrested in neighborhoods other than the neighborhood in which their crime was committed or multiple arrests are made for the same crime.

The clearance rate is another common measure of the risk of arrest and punishment, which defines the rate of arrest using only arrests that can be linked to specific crimes solved. An advantage of such a measure is that it is a more precise measure of the risk of being caught for committing a specific crime. On the other hand, the clearance rate may not be particularly important to a criminal that is a repeat offender who engages in a range of crimes (e.g., multiple robberies, burglaries, drug sales). Then the criminal's primary concern may be to avoid any involvement with the legal system, whether or not ultimately leading to punishment for a specific crime they have committed. In any case, clearance information is not contained in the 1987 data used here.

Eighteen Police Reporting Areas (*PRA*s) spanning L.A. are chosen as fixed effects for grouping nearby neighborhoods, PRA_{Area}. Each fixed effect is an indicator variable that identifies about 35 nearby neighborhoods covering about 26 square miles (areas about 5 miles across). These areas are small enough for criminals and potential victims of crime to reasonably exhibit some

mobility in their choice of neighborhoods for activity. Since fixed effects group neighborhoods by proximity, they may account for unobservable influences on crime rates that are systematic to neighborhoods in a group, and also function as a crude control for spatial autocorrelation. *PRA*s also provide a good basis for grouping neighborhoods because they correspond to an LAPD administrative structure within which police resources may be re-allocated between neighborhoods in response to differences in neighborhood crime rates. Each *PRA* contains one police station, except the downtown central *PRA* that has three stations, one of which is the citywide police headquarters, Parker Center.

More Recent Property Crime and Arrest Data for Police Reporting Areas

This paper also presents property crime and arrest rate statistics from more recent years, 1997-2003, at the aggregate level of each *PRA* (LAPD, 2005). Data for 1987 are aggregated to the *PRA* level to enable comparison with the more recent data.

Findings

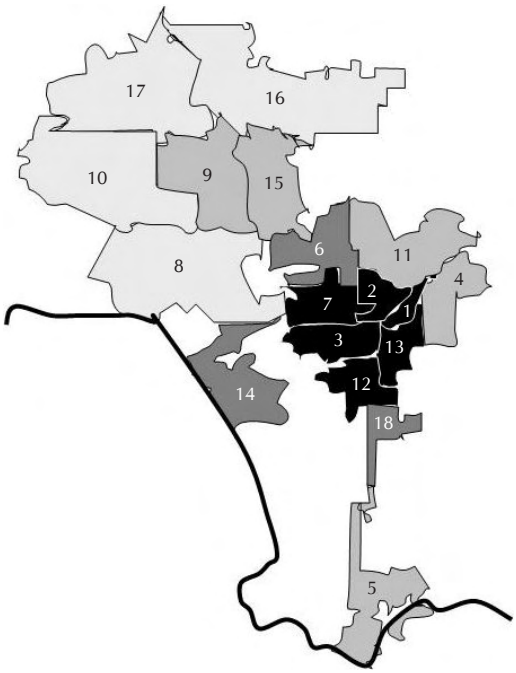
The Relationship between Property Crime and Measures of Criminal Opportunities

Figures 2 and 3 show the overall patterns of aggregated property crimes and household income in L.A. in 1987 by Police Reporting Area (*PRA*). Crime is very high, greater than 1,000 crimes annually per square mile, in downtown and inner city neighborhoods of the Central, Rampart, Southwest, Wilshire, 77th Street, and Newton Street *PRA*s (see Figure 2). The Central *PRA* has 3,474 property crimes per square mile and the Rampart *PRA* has 2,372 property crimes per square mile! In contrast, the rate of crime is under 300 crimes per square mile in the *PRA*s that are the farthest distance from the central city, West L.A., West Valley, Foothill, and Devonshire *PRA*s. Higher crime towards the city center has been a pattern typical of urban areas for the last century (Shaw and McKay, 1942).

Figure 3 shows the distribution of average household income of neighborhood residents in 1987 by *PRA*. Higher property crime and lower average household income generally correspond at this aggregated geographic level, both tending to be higher towards the inner city (compare Figures 2 and 3). For example, the neighborhood at the 80th percentile of the property crime distribution is located in the Newton Street *PRA* and has over four times the rate of property crime per square mile as the neighborhood at the 20th percentile of the property crime distribution which is located in the Foothill *PRA* (1,420.5 property crimes per square mile versus 303.2 property crimes per square mile). The average household

Figure 2. Property Crimes per Square Mile in 1987 by Police Reporting Area

1	Central	3,474
2	Rampart	2,372
3	Southwest	1,546
4	Hollenbreck	589
5	Harbor	353
6	Hollywood	969
7	Wilshire	1,258
8	West L.A.	203
9	Van Nuys	562
10	West Valley	282
11	Northeast	450
12	77th Street	1,133
13	Newton Street	1,413
14	Pacific	736
15	N. Hollywood	530
16	Foothill	168
17	Devonshire	191
18	Southeast	843

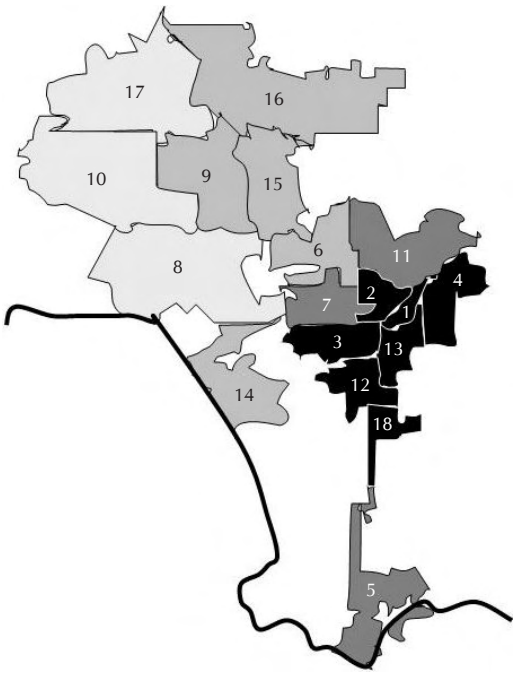


Legend

- Low: 1–300
- Medium: 301–600
- High: 601–1000
- Very high: >1000

Figure 3. Average Household Income in 1987 by Police Reporting Area

1	Central	$25,792
2	Rampart	$23,088
3	Southwest	$24,949
4	Hollenbreck	$28,697
5	Harbor	$37,624
6	Hollywood	$40,874
7	Wilshire	$39,769
8	West L.A.	$94,738
9	Van Nuys	$44,101
10	West Valley	$61,953
11	Northeast	$38,195
12	77th Street	$27,117
13	Newton Street	$22,355
14	Pacific	$49,772
15	N. Hollywood	$45,718
16	Foothill	$44,688
17	Devonshire	$62,066
18	Southeast	$24,228



Legend

- High: over $60,000
- Medium: $40,000 to $50,000
- Low: $30,000 to $40,000
- Very low: Under $30,000

income of residents in the neighborhood at the 80th percentile of the property crime distribution is about half that of residents in the neighborhood at the 20th percentile of the property crime distribution ($24,573 versus $55,335 annually; see Table 1).

Multiple regression models with controls for neighborhood characteristics and fixed effects for each *PRA* show patterns consistent with the aggregate picture. The estimated coefficient of -0.35 on the average household income of neighborhood residents indicates a 0.35 percent higher rate of property crime per square mile for each one percent decrease in average household income in a neighborhood (since dependent and independent variables in the property crime equation are logged; see Table 2, Step 3 and Table 3). Average household income of neighborhood residents is also significantly negatively related to each separate type of felony crime considered here and is largest for robbery (see Table 3). Evaluated at the mean values of L.A. neighborhoods, each one percent decrease in average household income in a neighborhood (a $460 annual decrease in 1989 dollars) is associated with 3.5 more property crimes per square mile, 0.7 more robberies, 0.9 more burglaries, 0.6 more auto thefts, and 1.2 more felony thefts per square mile each year in a neighborhood.

The estimated elasticity of the neighborhood rate of property crime to the average household income of neighborhood residents is not constant across the city. Estimates range from –.23 to –.40 when the neighborhoods in any given *PRA* are dropped from the estimation. This demonstrates the limits of average resident income for consistently reflecting local populations of criminals. However, other measures included in the model also help to identify higher populations of local criminals. Residential density and the percentage of residents who are African-American, which may proxy for poverty rates not included in the model, are associated with significantly higher crime (see Table 2, Step 3 and Table 3).

The Relationship between Property Crime and Measures of Criminal Motives

A correspondence between the crime rate and jobs per square mile is not obvious at an aggregated geographic level by *PRA*. The city center has the greatest concentration of jobs per square mile as well as the highest crime rates per square mile (compare Figures 2 and 4). Outside downtown areas, however, there appears to be a tendency for jobs to be located outside of higher crime areas. For example, jobs per square mile are lowest in the 77th Street *PRA* that includes South Central and has a very high crime rate, while jobs per square mile are fairly high in the West L.A. *PRA* that has a very low crime rate.

Regression models estimated with controls for neighborhood characteristics and fixed effects for each *PRA* show positive relationships between crime rates and jobs per square mile. Since the fixed area effects restrict the estimated relationships to variation between neighborhoods within *PRA*s, the positive estimates at this level are consistent with the hypothesized criminal preference to commit more crimes in nearby neighborhoods where criminal opportunities are greater. A one percent increase in jobs per square mile is, all else equal, significantly positively related to 0.22 percent higher rate of property crime overall, 0.29 percent higher rate of robbery, 0.28 percent higher rate of burglary, 0.21 percent higher rate of auto theft, and 0.21 percent higher rate of felony theft per square mile (see Table 3). Evaluated at the mean values of L.A. neighborhoods, 64.5 more jobs per square mile attract 2.2 more property crimes, 0.3 more robberies, 0.6 more burglaries, 0.5 more auto thefts, and 0.8 more felony thefts per square mile. Other measures of economic activity in a neighborhood are also significantly positively related to property crime rates, such as the presence of a regional shopping center or a downtown location (see Table 2, Step 3).

The presence of a high school in a neighborhood is also related to higher crime. Venkatesh (2005) has found anecdotal evidence that conflict between younger gang members tends to occur around high schools. High schools may provide property criminals of school age with mobility to and familiarity with the neighborhood containing the high school.

Table 1. Descriptive Statistics for Neighorhood Variables in Los Angeles in 1987

(n = 636)

Variable	Mean	Standard error	Value at 20th percentile of property crime distribution	Value at 80th percentile of property crime distribution
Property crime/sq. mi.	998.6	1037.2	303.2	1420.5
Robbery/sq. mi.	114.2	163.5	19.7	295.7
Burglary/sq. mi.	219.1	291.9	50.8	197.1
Auto theft/sq. mi.	254.5	262.8	70.5	411.7
Felony theft/sq. mi.	410.8	429.9	162.3	516.0
Assault/sq. mi.	153.0	200.0	24.6	353.7
Property crime arrest rate	13.2 %	10.9	0.1 %	26.9 %
Robbery arrest rate	38.0 %	88.0	0.1 %	29.4 %
Burglary arrest rate	9.6 %	10.0	0.1 %	11.8 %
Auto theft arrest rate	18.4 %	36.0	0.2 %	46.5 %
Felony theft arrest rate	9.0 %	8.0	0.0 %	15.7 %
Assault arrest rate	62.4 %	106.7	0.8 %	75.4 %
Jobs per square mile	6,446	16,004	488	800
Household income	$46,010	$31,352	$55,335	$24,573
Resident population density	13,332	10,155	9,672	25,679
Percent African-American residents	14.9 %	23.2	3.0 %	37.6 %
Percent Hispanic residents	36.4 %	27.1	51.4 %	63.9 %
Percent age 16-19 residents	5.7 %	4.3	7.3 %	7.2 %
Percent age 20-29 residents	21.6 %	7.5	19.2 %	24.1 %
Ratio female/male residents	1.01	.13	0.97	0.97
Percent high school dropouts aged 16-19	17.5 %	13.0	25.4 %	33.8 %
Downtown	1.4 %	11.8	0	0
Regional shopping center	2.2 %	14.7	0	0
Local shopping center	3.1 %	17.5	0	0
High school	6.0 %	23.7	0	0
College	1.9 %	13.6	0	0
Airport	0.8 %	8.8	0	0
Sports center	0.6 %	7.9	0	0
Railroad yard	0.5 %	6.9	0	0
Freeway exit	28.6 %	45.2	1	0
PRA			Foothill	Newton St.
Square miles	0.75	1.22	0.61	0.17

Since the estimated relationship between property crime and jobs per square mile in the full model in Table 2 is, on net, positive, the simultaneous response of jobs fleeing neighborhoods with higher crime rates appears to be a relatively smaller effect than the attraction of criminal activity to jobs at the local level. Indeed, the estimated elasticity of the neighborhood crime rate to jobs per square mile is fairly robust to dropping the neighborhoods in any

Table 2. Generalized Least Squares Regressions on Property Crimes per Square Mile for L.A. Neighborhoods in 1987

(n = 636)

Estimates for first ten variables represent percent change in property crimes per square mile with respect to a one percent change in variable; estimates for remaining dummy variables are percentage change in property crimes per square mile when characteristic is present.

	Step 1			Step 2			Step 3		
Control variables	β		t	β		t	β		t
Arrest rate	0.41	*	5.21	0.32	*	3.33	-0.13	*	-1.97
Jobs per square mile							0.22	*	10.91
Household Income							-0.35	*	-3.33
Resident population density							0.76	*	16.26
Percent African-American residents							0.05	*	2.20
Percent Hispanic residents							-0.07		-1.30
Percent age 16-19 residents							-0.12	**	-1.86
Percent age 20-29 residents							0.18	**	1.79
Ratio female/male residents							0.10		0.97
Percent high school dropouts							0.01		0.86
Downtown							1.07	*	6.29
Regional shopping center							0.69	*	3.64
Local shopping center							0.07		0.74
High school							0.21	*	3.65
College							-0.17		-1.21
Airport							0.15		0.82
Sports center							0.08		0.76
Railroad yard							-0.31		-1.41
Freeway exit							-0.03		-0.80
1. Central (omitted)									
2. Rampart				-0.58	**	-1.64	-0.33		-0.93
3. Southwest				-1.04	*	-2.87	-0.15		-0.43
4. Hollenbeck				-1.93	*	-5.38	-0.49		-1.33
5. Harbor				-2.39	*	-6.23	-0.52		-1.44
6. Hollywood				-1.00	*	-2.49	-0.23		-0.63
7. Wilshire				-1.02	*	-2.80	-0.25		-0.71
8. West L.A.				-2.05	*	-4.89	-0.56		-1.53
9. Van Nuys				-1.93	*	-5.31	-0.58		-1.61
10. West Valley				-2.54	*	-6.86	-0.58		-1.60
11. Northeast				-1.89	*	-5.19	-0.46		-1.29
12. 77th Street				-1.44	*	-4.10	-0.10		-0.28
13. Newton Street				-1.34	*	-3.75	-0.31		-0.89
14. Pacific				-1.32	*	-3.49	-0.34		-0.94
15. North Hollywood				-1.92	*	-5.41	-0.45		-1.25
16. Foothill				-2.94	*	-7.87	-0.52		-1.41
17. Devonshire				-2.76	*	-6.82	-0.61	**	-1.69
18. Southeast				-1.75	*	-4.86	-0.15		-0.40
Constant	7.39	*	40.30	8.96	*	22.95	1.46		1.04
R Squared	0.0893			0.47			0.9005		

* p < .05; ** p < .10

Table 3. Generalized Least Squares Estimates of Elasticity of Property Crime to Household Income and Jobs per Square Mile for L.A. Neighborhoods in 1987

(n = 636)

Model controls for arrest rate, fixed effect indicators for Police Reporting Areas (PRA) and demographic and neighborhood characteristics listed in Table 1.

		Household income		Jobs per square mile	
Control variables	**R^2**	β	t	β	t
Property crime	.9005	-0.35 *	-3.33	0.22 *	10.91
Robbery	.8712	-0.60 *	-4.15	0.29 *	10.48
Burglary	.8297	-0.41 *	-3.17	0.28 *	11.99
Auto theft	.8857	-0.25 *	-2.29	0.21 *	8.34
Felony theft	.8800	-0.28 *	-2.41	0.21 *	9.73
Assault	.9139	-0.57 *	-5.04	0.13 *	3.98

* $p < .05$; ** $p < .10$

given *PRA* from the data (ranging only from 0.20 to 0.23). One factor that may lead to this result is that the measure of jobs per square mile is lagged one year (1986) prior to the crime rate (1987) so that endogenous responses of potential victims are not captured by the estimate. Indeed, lagging related variables is one technique that researchers have used to deal with endogeneity (Marvell and Moody, 1996). Although aggregate patterns outside of downtown areas suggest some tendency for jobs to locate outside of high crime, low income areas, no evidence of this effect is found in the multiple regression estimates.

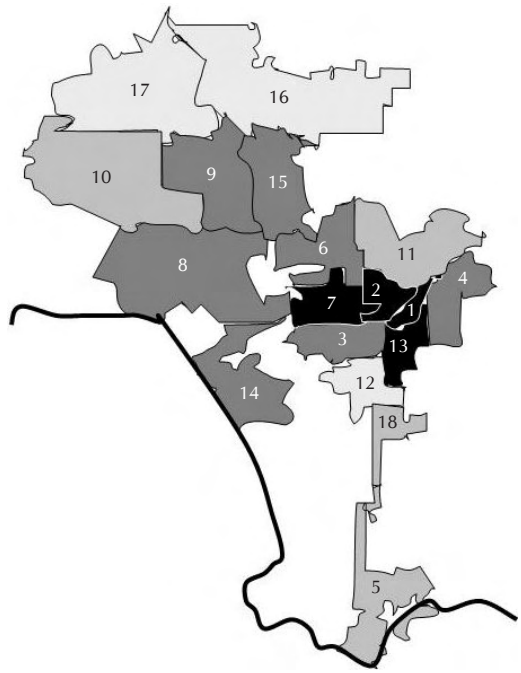
The Relationship between Property Crime and Property Crime Arrest Rates

There is a very wide distribution of arrest rates in L.A. in 1987 (see Figure 5). Property crime arrest rates are less than 10 percent in the 6 *PRA*s at the low end of the distribution that are on the northwest side of the city and near coastal areas. By contrast, arrest rates are more than 17 percent in the 6 *PRA*s at the high end of the distribution found in the center and southeast inner city.

Arrest rates in 1987 tend to be higher where the

Figure 4. Jobs per Square Mile in 1987 by Police Reporting Area

1	Central	66,018
2	Rampart	18,100
3	Southwest	5,728
4	Hollenbreck	5,888
5	Harbor	2,353
6	Hollywood	3,965
7	Wilshire	7,459
8	West L.A.	3,179
9	Van Nuys	5,364
10	West Valley	2,416
11	Northeast	2,414
12	77th Street	1,616
13	Newton Street	11,392
14	Pacific	5,378
15	N. Hollywood	3,062
16	Foothill	891
17	Devonshire	1,908
18	Southeast	2,142



Legend

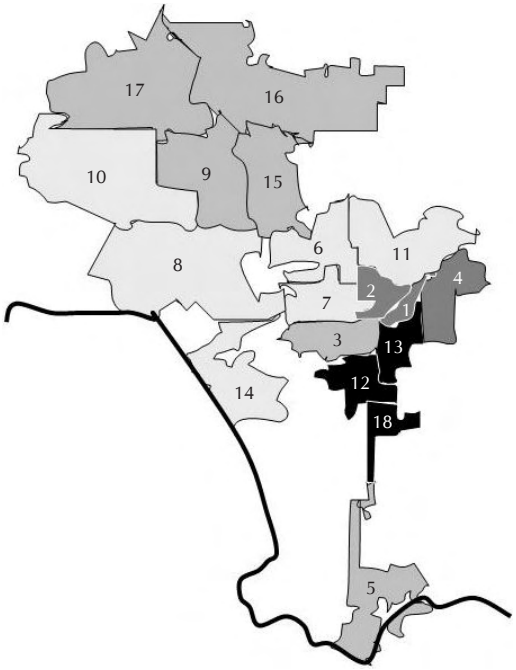
- Low: Less than 2,000
- Medium: 2,000–3,000
- High: 3,000–6,000
- Very high: More than 6,000

Figure 5. Property Crime Arrest Rates in 1987 by Police Reporting Area

1	Central	18.0 %
2	Rampart	17.5 %
3	Southwest	13.3 %
4	Hollenbreck	17.4 %
5	Harbor	14.0 %
6	Hollywood	9.5 %
7	Wilshire	9.5 %
8	West L.A.	7.0 %
9	Van Nuys	12.1 %
10	West Valley	8.9 %
11	Northeast	9.5 %
12	77th Street	20.8 %
13	Newton Street	22.2 %
14	Pacific	5.1 %
15	N. Hollywood	13.5 %
16	Foothill	14.6 %
17	Devonshire	10.5 %
18	Southeast	29.2 %

Legend

Low: 0%–10%
Medium: >10%–15%
High: >15%–19%
Very high: >19%



crime rate is higher, and particularly where average resident income is lower. The raw correlation between property crime and arrest rates across the 636 neighborhoods of L.A. in 1987 is 0.11 and significant (see Table 5). The *PRA*s with the highest arrest rates are Southeast (29.2 percent), 77th Street (20.8 percent), and Newton Street (22.2 percent). Arrest rates are also high at around 17 percent in the downtown and Hollenbeck areas just east of downtown. These *PRA*s have average household income below most of the city, under $30,000 annually. However, the Wilshire *PRA* has the 5th highest crime rate in the city at 1,258 crimes per square mile annually as well as a large percentage of minority residents, and yet its property crime arrest rate is only 9.5 percent. Wilshire can be distinguished from other high crime *PRA*s as a relatively affluent area with an average household income of nearly $40,000 annually in 1989 dollars. Thus, arrest rates for property crime are disproportionately high for the lowest income *PRA*s, irrespective of their high minority composition and crime rates. This may well be related to an overall LAPD strategy to combat the epidemics of violent gang activity and crack dealing that particularly distinguished the poorest communities from other high crime areas of L.A. in 1987 (Alonso, 2005). Nonetheless, a strategy that resulted in disproportionately high property crime arrest rates for low income, minority neighborhoods surely contributed to the perception that the LAPD used heavier handed tactics with minorities generally.

Similar to the aggregate picture, multiple regression techniques using neighborhood level data but excluding control variables and fixed area effects show that property crime is significantly higher by 0.41 percent for neighborhoods where arrest rates are one percent higher (see Tables 2 and 4, Step 1). When indicators for each *PRA* are added to the regression model to account for the average level of the crime rate in each *PRA*, the relationship between property crime and arrest rates shrinks to 0.32 percent and is still significant (see Tables 2 and 4, Step 2). Indicators for each *PRA* restrict the estimated relationship to reflect only variation within each *PRA*, which demonstrates that the correlation between higher arrest rates and higher crime rates is stronger for more distant neighborhoods across the city, but still present within *PRA*s.

In contrast, when multiple regression models are estimated with the full set of controls for neighborhood characteristics and fixed area effects for each *PRA*, the elasticity of the property crime rate to property crime arrest rates is -0.13 and significant at the 5 percent level (see Tables 2 and 4, Step 3). When the full model is applied to separate types of property crime, a one percent increase in the rate of arrest in a neighborhood significantly reduces auto theft by 0.11 percent and felony theft by 0.12 (see Table 4, Step 3). The elasticity of crime to the arrest

Table 4. Generalized Least Squares Estimates of Elasticity of Property Crime to Arrest Rate for L.A. Neighborhoods in 1987 adding Control Variables in Stepwise Procedure

(n = 636)

Step 1 controls only for arrest rate. Step 2 controls for arrest rate and indicators of Police Reporting Areas. Step 3 controls for arrest rate, fixed effect indicators for Police Reporting Areas and all demographic and neighborhood characteristics listed in Table 1.

	Step 1			Step 2			Step 3		
Control variables	β	t	R^2	β	t	R^2	β	t	R^2
Property crime	0.41 *	5.21	.089	0.32 *	3.33	.470	-0.13 *	-1.97	.901
Robbery	0.42 *	4.86	.073	0.23 *	3.24	.549	-0.04	-1.25	.871
Burglary	0.28 *	4.94	.069	0.19 *	3.28	.340	-0.03	-1.01	.830
Auto theft	0.17 *	2.56	.026	0.66	0.91	.450	-0.11 *	-2.42	.886
Felony theft	0.21 *	3.39	.031	0.19 *	3.22	.442	-0.12 *	-2.97	.880
Assault	0.40 *	2.07	.029	0.30 **	1.81	.525	-0.27 *	-3.02	.914

* $p < .05$; ** $p < .10$

rate for robbery and burglary is also negative, but the estimates are not significant (see Table 4, Step 3). Since the full model controls for neighborhood characteristics and fixed area effects, the estimated coefficients measure effects of arrest rates on crime for nearby neighborhoods with similar jobs per square mile, household income, and other neighborhood characteristics.

Negative estimates in the full model are consistent with the predictions of the economic model of crime, which suggests that higher arrest rates deter, displace, or remove criminal activity from neighborhoods at a local level. Negative estimates are also consistent with previous studies of the relationship between crime and arrest rates, which find arrest rates are simultaneously lower where crime rates are higher as a result of police resources being locally overwhelmed by higher criminal activity (Ehrlich, 1973; Glaser and Sacerdote, 1999). As discussed above, some of the variation in arrest rates should be independent of property crime rates due to the LAPD practice of making disproportionately higher rates of arrest in the lowest income, minority neighborhoods irrespective of their crime rates. Thus, it is reasonable to infer that some of the measured negative relationship between crime and arrest rates reflects deterrence and displacement of criminal activity, rather than just simultaneity.

The contrast between the *negative* relationship between property crime and arrest rates in the regression model with the full set of controls and fixed effects for each *PRA* compared to the *positive* relationship in the regression model without any controls suggests that there is positive simultaneity between property crime and arrest rates. This is consistent with the direction of simultaneity found in the literature on crime and police levels (Kovandzic and Sloan, 2002; Levitt, 1997). It also indicates that when estimates are based on wider geographic distances across *PRA*s, rather than more local distances within *PRA*s, the estimates begin to reflect differences in the level of police efforts rather than responses of criminal activity to arrest rates. This makes sense in the context of neighborhoods within a city where police manpower is under a common police administration that may allocate resources across the entire city but where criminals tend to commit crime locally on their own "turf."

Evaluated at the mean values of crime and arrest rates for L.A. neighborhoods, the arrest of one property criminal translates into 0.98 fewer property crimes per square mile annually in a neighborhood.[11] However, the average values of crime and arrest rates across the city are misleading for many areas of L.A. since arrest rates tend to be much higher in higher crime neighborhoods, especially when they have lower income minority residents. When evaluated at the mean values for crime and arrest rates of the neighborhood at the 80th percentile of the property crime distribution, the arrest of one property criminal is associated with only 0.48 fewer property crimes per square mile annually. In contrast, the arrest of one property criminal in a lower crime neighborhood at the 20th percentile of the property crime distribution is associated with 1.84 fewer property crimes per square mile annually. This is because the much higher arrest rate in the high crime neighborhood at the 80th percentile of the property crime distribution (26.9%) is affected far less by a single additional arrest than the lower arrest rate in the lower crime neighborhood at the 20th percentile of the property crime distribution (7.0%).

The estimated elasticity of the neighborhood crime rate to the neighborhood's arrest rate is not constant across the city. When neighborhoods in any given *PRA* are dropped from the data, estimates based on the remain-

der of the city range from -.08 to -0.15. In addition, estimates remain significant at the 5 percent level only when dropping those *PRA*s that are on the northwest side of the city (*PRA* 8, 10, 15, and 17) or when dropping the 77th Street *PRA*. This suggests that criminals in these *PRA*s are less responsive to changes in arrest rates. Conversely, it implies that criminals are more responsive to arrest rates in downtown and central city areas, with the exception of the 77th Street *PRA*. The 77th Street *PRA* may be a special case, since it is distinguished from other high crime inner city areas by having extremely few jobs per square mile.

Trends in Property Crime and Arrest Rates from 1997 to 2003

Figures 6 and 7 show the pattern of crime and arrest rates in L.A. by *PRA* for 1997, 10 years after the neighborhood level data analyzed in this paper. Crime is considerably lower across the city by 1997 (after peaking in 1992, the year of the L.A. riots and a subsequent gang truce). The rate of property crime per square mile for the average *PRA* is 948 crimes per square mile in 1987 compared to 577 crimes per square mile in 1997. Only three *PRA*s have property crimes per square mile above 1,000 annually in 1997 as compared to six *PRA*s in 1987. Still the distribution of crime across the city is similar, tending to be highest towards the inner city and in historically lower income areas.

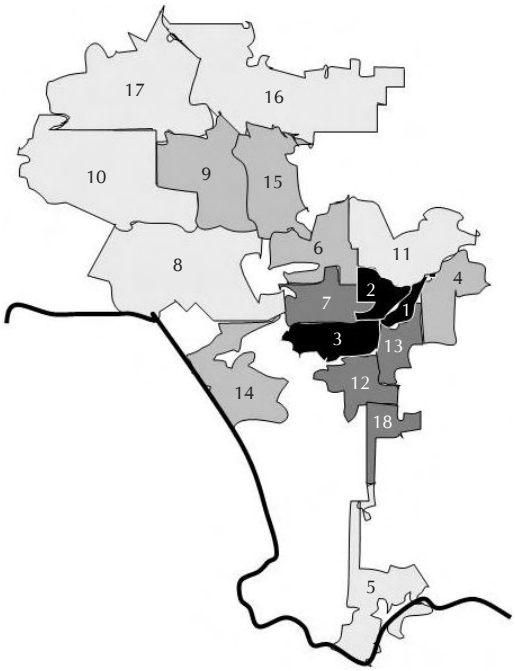
The average rate of arrest by *PRA* rose between 1987 and 1997 from 14.0 percent to 15.0 percent. However, the wide range of property crime arrest rates between *PRA*s declined from 1987 to 1997 (see Figure 7). The Southeast *PRA* has the highest average arrest rate in 1987 at 29.2 percent, and the Pacific *PRA* has the lowest at 5.1 percent. By 1997, the 77th Street *PRA* has the highest average arrest rate at 19.5 percent, and the Pacific *PRA* has the lowest at 5.4 percent. Positive correlations between crime and arrest rates at the level of *PRA*s become larger and more significant in more recent years, rising from 0.36 in 1987 to 0.41 in 1997 and to 0.60 in 2003 (see Table 5). This trend appears to be driven by higher arrest rates for more serious property crimes, robbery, burglary, and auto theft; since the correlation between felony theft and felony theft arrest rates is small, insignificant, and changes signs in different years. This suggests that in the more recent decade, the LAPD has a more systematic practice of higher property crime arrest rates for higher property crime neighborhoods that is driven by the most serious property crimes.

Policy Implications

In the full regression model for 1987 with controls

Figure 6. Property Crimes per Square Mile in 1997 by Police Reporting Area

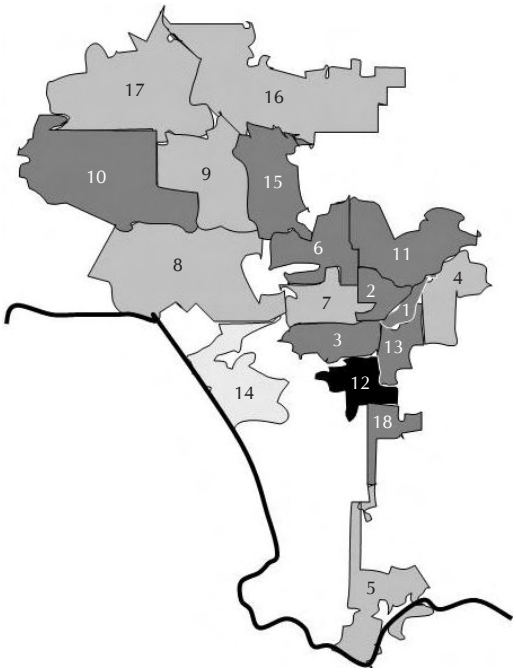
1	Central	1,399
2	Rampart	1,098
3	Southwest	1,063
4	Hollenbreck	429
5	Harbor	289
6	Hollywood	558
7	Wilshire	955
8	West L.A.	138
9	Van Nuys	396
10	West Valley	229
11	Northeast	298
12	77th Street	715
13	Newton Street	858
14	Pacific	546
15	N. Hollywood	404
16	Foothill	135
17	Devonshire	181
18	Southeast	687



Legend
- Low:1–300
- Medium: 301–600
- High: 601–1000
- Very high: >100

Figure 7. Property Crime Arrest Rates in 1997 by Police Reporting Area

1	Central	17.6 %
2	Rampart	17.7 %
3	Southwest	17.0 %
4	Hollenbreck	13.7 %
5	Harbor	10.4 %
6	Hollywood	15.2 %
7	Wilshire	14.7 %
8	West L.A.	12.0 %
9	Van Nuys	14.6 %
10	West Valley	17.8 %
11	Northeast	15.6 %
12	77th Street	19.5 %
13	Newton Street	18.3 %
14	Pacific	5.4 %
15	N. Hollywood	15.2 %
16	Foothill	14.4 %
17	Devonshire	14.8 %
18	Southeast	16.9 %



Legend

- Low: 0%–10%
- Medium: >10%–15%
- High: >15%–19%
- Very high: >19%

for neighborhood characteristics and fixed area effects, property crime rates are higher in neighborhoods with higher jobs per square mile, lower arrest rates, and lower average household income of neighborhood residents. At an aggregate level by *PRA*, rates of property crime also correlate with lower average household income of neighborhood residents and with more jobs per square mile, although there may be a reverse correlation between crime and jobs outside of downtown areas. In contrast to the full regression model that measures more local relationships, average property crime rates at the level of *PRA* are higher where arrest rates are higher, especially where the average household income of residents is lower.

Since most property criminals are, by definition, active in the higher crime neighborhoods where jobs per square mile are sometimes lower and arrest rates are typically higher, the advantage to criminal activity in the higher property crime neighborhoods, according to property criminals' preferences measured in the full model, is the proximity of these neighborhoods to criminals' likely neighborhoods of residence (e.g., neighborhoods whose residents have lower average household incomes). This parallels spatial mismatch theories of the legitimate labor market in which the lower incomes of minorities who reside in inner city neighborhoods results from a mismatch between their neighborhoods of residence and

Table 5. Raw Correlations between Property Crimes per Square Mile and Arrest Rates, by Type of Crime

Correlations are estimated across data aggregated to level of 18 Police Reporting Area, except for first column which is estimated across 636 neighborhoods.

Control variables	1987 all	1987	1997	1998	1999	2000	2001	2002	2003
Property crime	.11 *	.36	.41 **	.41 **	.22	.42 **	.59 *	.66 *	.60 *
Robbery	-.01	.38	.05	.40	.11	.48 *	.51 *	.41 **	.46 **
Burglary	.05	.37	.35	.22	.21	.49 *	.68 *	.66 *	.62 *
Auto theft	-.04	.19	.39	.40 **	.53 *	.53 *	.59 *	.66 *	.47 *
Felony theft	-.03	.10	.05	.03	-.13	-.02	.13	.19	.24
Sample size	636	18	18	18	18	18	18	18	18

* $p<.05$; ** $p<.10$

the suburban neighborhoods with the most lucrative job opportunities (Holzer, 1991; Preston and McLafferty, 1999; Stoll, 1999).

The LAPD appears to take advantage of the limited local mobility of criminals by shifting arrest efforts from lower to higher property crime neighborhoods across the city, especially in more recent years. This strategy is warranted so long as the associated decline in police protection in lower property crime neighborhoods, necessitated by moving limited police resources to higher property crime neighborhoods, does not lead to the commission of more property crimes in lower property crime neighborhoods than are deterred by the addition of police resources in higher property crime neighborhoods. As noted above, using the 1987 estimates from the full model, the arrest of one more property criminal in the high crime neighborhood at the 80th percentile of the property crime distribution reduces crime by only 0.48 property crimes per square mile, while arresting one more property criminal in the low crime neighborhood at the 20th percentile of the property crime distribution decreases crime by 1.84 property crimes per square mile. Based on these citywide estimates, using police resources to arrest one more property criminal in the high crime neighborhood instead of the low crime neighborhood does not appear to reduce property crime for the city as a whole in L.A. in 1987, especially with arrest rates approaching 30 percent in some high crime areas. Indeed, presuming all other characteristics equal between neighborhoods, such a strategy should only have net benefits when arrest rates are higher in lower crime neighborhoods. On the other hand, if criminals in lower crime neighborhoods are less responsive to falling arrest rates (as is likely for the low crime *PRA*s 8, 10, 15 and 17, given results when dropping these *PRA*s from the estimation), then such a strategy could conceivably still lead to a net reduction in crime. It is, however, naïve to assess the practice of shifting police arrest efforts to higher property crime neighborhoods solely based on the effect this may have on property crime, since more important objectives of the police include the control of violent crime. Property crime arrest rates may very well have been disproportionately high in lower income minority neighborhoods as a spillover effect from police efforts to fight violent gang activity and the crack epidemic that hit these neighborhoods particularly hard in the late 1980s.

Conclusion

Estimates at the neighborhood level in a multiple regression model of neighborhood property crime rates that uses a full set of controls for neighborhood characteristics and fixed area effects for *PRA*s show that average household income of neighborhood residents and jobs per square mile separately capture motivations and opportunities for crime commission as expected from the economic model of property crime. A significant negative relationship is measured between property crime and arrest rates in the full model, which may reflect deterrence, displacement, or elimination of property criminals. On the other hand, a significant positive relationship between property crime and arrest rates is obtained when the model is estimated without any controls or fixed area effects for *PRA*s so that estimates are based on variation across the entire span of the city. This suggests that positive simultaneity between property crime and arrest rates may affect estimates that are based on wider geographic distances or when data is aggregated from local units of observation to the citywide level. It also suggests that the LAPD had a practice of higher arrest rates in higher crime neighborhoods in 1987, a practice which appears to be more systematic in more recent years. However, these estimates should be viewed with caution since they are based on a single cross section of data for L.A. in 1987, use aggregate proxy variables, and do not explicitly model spatial autocorrelation between neighborhoods or the complex simultaneous relationships between crime, jobs, and arrest rates.

Endnotes

1. In modeling neighborhood selection probabilities, the following functional form satisfies the properties of probabilities, $c_n \geq 0$ and $\Sigma_n c_n = 1$: $c_n = NR_n / \Sigma_n NR_n$ (Marshak, 1960).

2. Assuming that a population of K property criminals in an area evaluate returns identically and commit crimes at a common rate, C, the expected aggregate number of property crimes supplied to the nth neighborhood in an area of N neighborhoods is: $C_n = C * K * (NR_n / \Sigma_n NR_n)$ for each $n = 1, \ldots N$. Based on a first order approximation of the net returns to crime in which components of net returns are multiplicative, the aggregate supply of property crime to each neighborhood depends on separate arguments for the factors that affect the net returns to crime. A neighborhood's aggregate supply of crime in logarithmic form is: $log\ (C_n) = log(NR_n) + log(C*K/(\Sigma_n NR_n))$. The second term in this equation contains factors that are constant from the decision point of the marginal criminal and so are subsumed into the intercept term for a given area of neighborhoods: $log\ (C_n) = \alpha + log\ (NR_n)$. The efficiency of estimates is also improved by estimat-

ing the residual covariance matrix with the Huber-White estimation procedure and by adjusting standard errors for robustness to sample size.

3. A vector of solution values for each neighborhood will exist, be unique, be stable, and have an interior solution over the range where the net return function has constant sign and decreasing returns to scale or increasing returns to scale that are small (Miyao and Shapiro, 1981). As will be discussed later in the paper and shown in Figure 1, the net return function has two portions with different slopes. Thus, a different equilibrium can be found in each portion (i.e., one with higher crime and one with zero or "low" crime).

4. Random effects are an alternative approach to fixed effects to account for average differences in dependent and predictive variables between different groupings of neighborhoods. Random effects use fewer degrees of freedom than fixed effects and allow more precise estimates. However, random effects can lead to biased estimates if the average differences between groups are not random, but are systematically different for particular groups (i.e., if neighborhoods in downtown *PRA* groupings have substantially higher crime than other neighborhoods, because those neighborhoods systematically differ from other neighborhoods in the city as might be due to the extreme density of residents and commuting jobs). Random effects are not used in this paper because Hausman specification tests indicated that some estimates were systematically different when random effects were used instead of fixed effects. In particular, the estimated effect on the property crime rate due to average household income (used to measure criminal motivations) was negatively biased, which exaggerated its measured effect in a random effects model.

5. The model of neighborhood crime presented here does not explicitly model spatial auto-correlation between crime rates in contiguous neighborhoods, nor does it explicitly include measures of key factors from contiguous neighborhoods. However, each neighborhood level unit of observation is, at root, an arbitrarily defined geographical division of the wider city and might be viewed as an aggregate of potentially smaller units of observation, such as city blocks. Framed in this way, a spillover effect of crime from nearby neighborhoods may be a measurement issue. In general, mis-measurement of dependent or independent variables should increase the unexplained variance in the model, resulting in smaller and less significant but nonetheless unbiased estimates (Greene, 2000).

6. Alternatively, jobs could also provide more positive role models for youth considering crime in a neighborhood and thus have an effect of *reducing* crime in a neighborhood. By their nature, aggregate proxy measures often have conflicting effects. It seems that jobs should primarily function as a measure of potential targets for crime, since residents in a neighborhood are likely to be more influential role models for criminals than workers who are more transient members of the community.

7. Another scenario that can cause negative simultaneity is if criminals are more likely to be arrested in high crime neighborhoods where they live, but visit both high and low crime neighborhoods of the area to commit crimes.

8. Another source of positive simultaneity between crime and arrest rates may come from an upward bias in crime reporting when there is greater police staffing in a locality (Levitt, 1998a). However, this seems unlikely in the highest crime, minority neighborhoods of L.A. where the police were unpopular.

9. Neighborhood crime rate equations are also estimated for assault for 1987 since these data were available.

10. I thank current and former members of the Economics Department of the University of California at Santa Barbara for compiling the crime and arrest data from paper records and matching it with census data and California Department of Employment data. This data set is available from the author by request.

11. The unit change in property crime rate for a unit change of one arrest for a given neighborhood is calculated by simply dividing the estimated elasticity (from Table 2, Step 3) by the arrest rate for that neighborhood: -0.98 property crimes per square mile = -0.13 elasticity estimate / 0.132 arrest rate.

References

Alonso, Alejandro A. 2005. *African-American Street Gangs in Los Angeles*. [Online]. Available: http://www/nagia.org/Crips_Bloods.htm.

Becker, Gary S. 1968. "Crime and Punishment: An Economic Approach." *Journal of Political Economy* 76:169-217.

Cannon, Lou. 1999. *Official Negligence: How Rodney King and the Riots Changed Los Angeles and the LAPD*. New York, NY: Random House.

Comanor, William S. and Llad Phillips. 1995. "The Impact of Income and Family Structure on Delinquency." *Working Paper #7–95*, Department of Economics, University of California at Santa Barbara, Santa Barbara, CA.

Dugan, Laura, Daniel S. Nagin and Richard Rosenfeld. 2003. "Exposure Reduction or Retaliation? The Effects of Domestic Violence Research on Intimate-Partner Homicide." *Law and Society Review* 37:169-198.

Ehrlich, Issac. 1973. "Participation in Illegitimate Activities: A Theoretical and Empirical Investigation." *Journal of Political Economy* 81:521-565.

Federal Bureau of Investigation. 1990. *Crime in the United States, 1990.* Washington, DC: U.S. Department of Justice.

Fiorentini, Gianluca and Sam Peltzman. 1995. "Introduction." Pp. 1-30 in *The Economics of Organised Crime*, edited by G. Fiorentini and S. Peltzman. Cambridge, UK: Cambridge University Press.

Glaser, Edward L. and Bruce Sacerdote. 1999. "Why is There More Crime in Cities?" *Journal of Political Economy* 107:225-258.

Greene, William H. 2000. *Econometric Analysis, Fourth Edition.* Upper Saddle River, NJ: Prentice-Hall.

Holzer, Harry J. 1991. "The Spatial Mismatch Hypothesis: What has the Evidence Shown?" *Urban Studies* 28:105-122.

Kelling, George and Anthony Pate. 1974. *The Kansas City Preventive Patrol Experiment.* Washington, DC: The Police Foundation.

Kleck, Gary and Ted Chiricos. 2002. "Unemployment and Property Crime: A Target-Specific Assessment of Opportunity and Motivation as Mediating Factors." *Criminology* 40:649-679.

Kovandzic, Tomislav V. and John J. Sloan. 2002. "Police Levels and Crime Rates Revisited: A County-level Analysis from Florida (1980-1998)." *Journal of Criminal Justice* 30:65-76.

Levitt, Steven D. 1997. "Using Electoral Cycles in Police Hiring to Estimate the Effect of Police on Crime." *American Economic Review* 87:270-290.

Levitt, Steven D. 1998a. "The Response of Crime Reporting Behavior to Changes in the Size of the Police Force: Implications for Studies of Police Effectiveness Using Reported Crime Data." *Journal of Quantitative Criminology* 14:62-81.

Levitt, Steven D. 1998b. "Why Do Higher Arrest Rates Reduce Crime: Deterrence, Incapacitation, or Measurement Error?" *Economic Inquiry* 36:353-72.

Los Angeles Police Department. 1987. *Monthly Report, a Summary of Crime and Arrests for the City of Los Angeles for the Month of (January – December)--1987*. Los Angeles, CA: Los Angeles Police Department.

Los Angeles Police Department. 2005. *Crime Statistics*. [Online]. Available: http://www.lapdonline.org/general_information/crime_statistics.

Los Angeles Police Department. 2006. *History of the LAPD, Chief Gates.* [Online]. Available: http://www.lapdonline.org/history_of_the_lapd/content_basic_view/1114

Ludwig, Jens, Greg J. Duncan and Paul Hirschfield. 2001. "Urban Poverty and Juvenile Crime: Evidence from a Randomized Housing Experiment." *Quarterly Journal of Economics* 116:665-679.

Marschak, Jacob. 1960. "Binary-Choice Constraints and Random Utility Indicators." Pp. 312-329 in *Mathematical Models in the Social Science*, edited by K. J. Arrow, S. Karlin and P. Suppeds. Palo Alto, CA: Stanford University Press.

Marvell, Thomas B. and Carlisle E. Moody. 1996. "Specification Problems, Police Levels, and Crime Rates." *Criminology* 34:609-646.

Miyao, Takahiro and Perry Shapiro. 1981. "Discrete Choice and Variable Returns to Scale." *International Economic Review* 22:257-273.

Phillips, Llad and Harold L. Votey, Jr. 1972. "An Economic Analysis of the Deterrent Effect of Law Enforcement on Criminal Activity." *Journal of Criminal Law, Criminology, and Police Science* 63:330-342.

Press, James S. 1971. *Some Effects of an Increase in Police Manpower in the 20th Precinct of New York City*. New York, NY: Rand Institute.

Preston, Valerie and Sarah McLafferty. 1999. "Spatial Mismatch Research in the 1990s: Progress and Potential." *Papers in Regional Science* 78:387-402.

Ralston, Roy. 1999. "Economy and Race: Interactive Determinants of Property Crime in the United States, 1958-1995: Reflections on the Supply of Property Crime." *American Journal of Economics and Sociology* 58:405-434.

Shaw, Clifford and Henry McKay. 1942. *Juvenile Delinquency and Urban Areas.* Chicago, IL: University of Chicago Press.

Stoll, Michael A. 1999. "Spatial Job Search, Spatial Mismatch, and the Employment and Wages of Racial and Ethnic Groups in Los Angeles." *Journal of Urban Economics* 46:129-155.

Venkatesh, Sudhir Alludi. 2005. Community Justice and the Gang: A Life Course Perspective. Working paper.

Wilson, William J. 1987. *The Truly Disadvantaged: The Inner City, the Underclass and Public Policy*. Chicago, IL: University of Chicago Press.

Wright, Richard T. and Scott H. Decker. 1994. *Burglars on the Job: Streetlife and Residential Break-ins*. Boston, MA: Northeastern University Press.

About the author:

John B. Davis is an economist with the litigation consulting firm ERS Group where he primarily researches allegations of discrimination in Title VII class action lawsuits using employer payroll records and other data, as well as issues including market concentration and trading behavior. He received his Ph.D. in Economics from the Department of Economics at the University of California Santa Barbara in the fall of 1999, where he concentrated his studies on the economic analysis of aggregate crime rate statistics, which is a continuing interest. This paper is based on his dissertation.

Contact information:

John B. Davis: ERS Group, 255 California Street, 12th floor, San Francisco, CA 94111; jdavis@ersgroup.com.