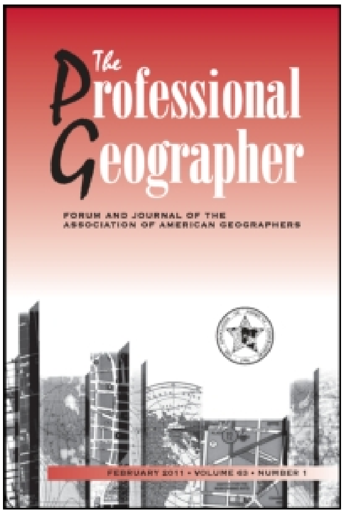

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Jeremy Mennis[a]; Philip W. Harris[a]; Zoran Obradovic[a]; Alan J. Izenman[a]; Heidi E. Grunwald[a]; Brian Lockwood[a]
[a] Temple University,

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The Effect of Neighborhood Characteristics and Spatial Spillover on Urban Juvenile Delinquency and Recidivism*

Jeremy Mennis, Philip W. Harris, Zoran Obradovic, Alan J. Izenman, Heidi E. Grunwald, and Brian Lockwood
Temple University

The objective of this research is to investigate the relationship between neighborhood characteristics and juvenile delinquency and recidivism (the proportion of delinquents who commit crimes following completion of a court-ordered program) in Philadelphia, Pennsylvania. We acquired data on collective efficacy, socioeconomic character, and crime for input into multivariate ordinary least squares (OLS) and spatial econometric regression analyses. Both delinquency and recidivism are concentrated in impoverished neighborhoods with violent crime, although this relationship is far stronger for delinquency than for recidivism. After accounting for the influence of crime and poverty, OLS regression results suggest that African American neighborhoods tend to exhibit higher delinquency rates, but lower recidivism rates, than other neighborhoods. Spatial lag models of recidivism rate indicate the presence of spatial spillover effects, which renders the influence of neighborhood racial character on recidivism rate not significant and which we speculate represents interaction among juveniles across neighborhood boundaries. **Key Words: geography of crime, juvenile delinquency, juvenile justice, juvenile recidivism.**

这项研究的目的是探讨在宾夕法尼亚州费城邻里之间的特点和青少年犯罪和重新犯罪的关系（在法庭下令计划完成后再犯罪的犯罪比例）。我们收集了集体效能，社会经济特征和犯罪的数据，把他们输入到多元普通最小二乘法（OLS）和空间计量经济学回归分析中。青少年犯罪和累犯这两种犯罪都集中在具有暴力犯罪行为的贫困社区，虽然青少年犯罪与贫困社区的关系远远强于青少年重新犯罪与贫困社区的关系。经过考虑犯罪和贫困的影响，OLS 回归结果表明，非裔美国人社区比其他街区容易出现较高拖欠率，但较低的再犯率。再犯率空间滞后模型显示了空间外溢效应的存在，这使得邻里种族特性对累犯率的影响不显著，我们推测这反应了跨社区边界的少年犯互动。**关键词：犯罪地理，少年犯罪，少年司法，少年重新犯罪。**

El objetivo de esta investigación es estudiar la relación que existe entre las características del vecindario con la delincuencia juvenil y reincidencia (la proporción de delincuentes que cometen crímenes tras completar un programa ordenado por los juzgados), en Filadelfia, Pensilvania. Obtuvimos información sobre eficacia colectiva, carácter socioeconómico y crimen a título de datos de entrada para análisis de mínimos cuadrados ordinarios (MCO) y regresión econométrica espacial multivariados. Tanto la delincuencia como la reincidencia se concentran en barriadas pobres afectadas por crimen violento, aunque esta relación es mucho más fuerte para delincuencia que para reincidencia. Luego de tomar en cuenta la influencia de crimen y pobreza, los resultados de la regresión MCO sugieren que los vecindarios afroamericanos tienden a exhibir tasas delincuenciales más altas, pero con menor reincidencia que lo registrado en otros vecindarios. Los modelos de rezago espacial de la tasa de reincidencia indican la presencia de efectos secundarios espaciales, lo cual hace que la influencia del carácter racial del vecindario sobre la tasa de reincidencia no sea significativa; especulamos que esto es indicativo de interacción entre juveniles a través de los límites barriales. **Palabras clave: geografía del crimen, delincuencia juvenil, justicia juvenil, reincidencia juvenil.**

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Estimating the effect of neighborhoods on the likelihood of juvenile delinquency recidivism (i.e., reoffense) has become increasingly important because "aftercare services" have proliferated for adjudicated youth. The ability to identify the effects of social disorganization on mitigating the gains from program participation is paramount to creating programs that promote positive physical, social, and affective youth development. At present, the field of juvenile justice has been limited to a search for programs that are effective across all environments and types of individuals, a search that employs traditional experimental designs and analyses (e.g., analysis of covariance [ANCOVA] for treatment effects and meta-analyses for summarizing across studies).

This approach to investigating the causes of juvenile recidivism does not consider that adolescent development and behavior can be supported and hampered by environmental forces (Elliott et al. 1996; Graber, Brooks-Gunn, and Petersen 1996; Brown 2004) or that delinquent youths are overrepresented in neighborhoods characterized by disorganization or criminogenic organization (Sampson 1997). To the extent that environmental forces impede social, emotional, and physical development, programs for delinquent youths can intervene to increase individual and social efficacy; these programs also serve as a buffer between youths and harmful external forces, so that natural developmental processes can continue. This view of intervention programs is particularly important in light of the finding that in neighborhoods characterized by poverty and social disorganization, residents are less willing to intervene when they see youths engaging in antisocial or unlawful acts (Sampson, Raudenbush, and Earls 1997). In addition to these environmental effects, recent research has demonstrated the potential deleterious effect of the actual institutional placements on child development (Steinberg, Chung, and Little 2004). This implies that aftercare services must address the youths' developmental needs, which might be aggravated by a period of institutionalization, as well as the external forces that inevitably compete with program effects.

We are currently engaged in a project funded by the National Institute of Justice (NIJ) that seeks to address how these various factors influence rehabilitation of delinquent youth. Specifically, we aim to develop and apply analytical techniques to understand how characteristics of the individual, neighborhood, and program interact to influence the likelihood of juvenile recidivism. In this article, we present results from an analysis that focuses specifically on environmental influences, by investigating the relationship between neighborhood characteristics and rates of juvenile delinquency and recidivism. We consider a variety of neighborhood characteristics, including collective efficacy, socioeconomic status, and crime. By focusing on the neighborhood level, we can combine information about neighborhoods with information about individuals and programs in understanding the causes of juvenile recidivism further along in the project.

Neighborhoods and Juvenile Delinquency

Wilson's (1987) book *The Truly Disadvantaged* stimulated a flurry of academic activity examining the role of neighborhood effects in producing a host of outcomes, including educational attainment, cognitive skills, early or unplanned pregnancy or parenting, and labor market success (e.g., Brooks-Gunn et al. 1993; Elliott et al. 1996; Simons et al. 1996; Kowaleski-Jones 2000; Rankin and Quane 2000, 2002; Simons et al. 2002). Concurrently, there was a resurgence of interest in social disorganization theory in the criminological literature (Shaw and McKay 1942). This literature highlighted the role of neighborhoods in promoting or prohibiting crime and delinquency through (a lack of) cohesion among neighbors and community-level social control (Simcha-Fagan and Schwartz 1986; Sampson and Groves 1989; Sampson 1992, 1997; Bursik and Grasmick 1993; Bursik 1998; Rountree and Warner 1999; Sampson, Morenoff, and Earls 1999; Veysey and Messner 1999; Markowitz et al. 2001). A current parallel strand of research on neighborhood effects has a more developmental focus and concentrates on the ways in which socialization and other family processes are constrained or enhanced by community characteristics (Brooks-Gunn et al. 1993; Elliott et al. 1996; Leventhal and Brooks-Gunn 2000; Rankin and Quane 2000, 2002).

Taken together, the social disorganization and developmental strands of research and theory on neighborhood effects would suggest at least two important ways that youth-serving agencies can suppress reoffending among adjudicated youths returning from placement. First, the presence of youth-serving agencies might foster stronger ties among community residents, increasing the level of community social control or willingness to become actively involved in addressing criminogenic factors (collective efficacy). Second, intervention programs can serve as a social buffer (Wilson 1987) against the collective effects of poverty, residential turnover, and family disruption; these, in turn, reduce social isolation and bring youths into contact with adults from outside the community who serve both to supervise and cosocialize adolescents. These agencies can provide youths with access to cultural and social enrichment opportunities that influence outcomes.

Despite the fact that adjudicated youths who are court-ordered to attend delinquent facilities are either served by programs in the community or, if institutionalized, return to their homes, correctional scholarship has neglected the role that neighborhoods play in reinforcing or weakening the treatment effects of these interventions. Examination of the outcomes for youth aftercare programs suggests that half of their clients reoffend at some time during the year after release, and one third return during this time to a more secure placement. Considering the rehabilitative context of the juvenile justice system, the lack of attention that the community pays to delinquency interventions is especially troubling.

Data and Preprocessing

Neighborhoods as a Unit of Analysis

The unit of analysis for this study is at the neighborhood level. We acquired data on collective efficacy, socioeconomic character, and crime from a variety of sources and aggregated these data up to rates for individual neighborhoods for statistical analysis. For the purpose of this study, neighborhoods are spatially defined according to a neighborhood boundary file developed by researchers at Temple University and used by a variety of organizations in the Philadelphia region. The file describes Philadelphia as a tessellation of forty-five nonoverlapping neighborhoods, most of the names and locations of which are commonly known to neighborhood residents. The roots of identity for many of the inner-city neighborhoods date from the nineteenth and even eighteenth centuries, whereas other neighborhoods represent more recent 1950s and 1960s housing developments. The boundaries of these neighborhoods are typically major natural and human-made features, such as rivers and major roads or highways. We eliminated the Center City neighborhood from the analysis, as this neighborhood is the downtown central business district and is an outlier in many of the neighborhood characteristics we theorize are related to delinquency and recidivism. In addition, there are relatively few delinquency cases that fall within Center City. Figure 1 shows a map of the neighborhoods, with the names marked for neighborhoods of particular import to this study.

We acknowledge that urban neighborhoods are by nature subjectively defined entities that often have ambiguous boundaries. However, finer units, such as Census tracts, have the problem of small counts of delinquency cases for calculating recidivism rate, defined as the proportion of delinquent cases that recidivate. Because we are interested in calculating recidivism rate over a set of spatial units, it is essential to have enough delinquency cases contained within each unit to make a reliable estimate of the rate. For example, given the delinquency data used in this study (described later), 197 out of the 381 tracts in Philadelphia (2000 Census) contain fewer than twenty delinquency cases, making estimates of recidivism rate in these tracts of questionable reliability. The neighborhood data set used here, although coarser than tracts and therefore perhaps more heterogeneous in character, represents a coherent set of spatial units that reflect long-held notions in Philadelphia about the boundaries of socioeconomically, culturally, and historically defined neighborhoods.

Delinquency and Recidivism

Data on juvenile delinquents were acquired from the Program Development and Evaluation System (ProDES) database, developed by the Crime and Justice Research Institute at Temple University under a contract with the City of Philadelphia. The ProDES database tracks juveniles assigned to court-ordered programs by the Family Court of Philadelphia

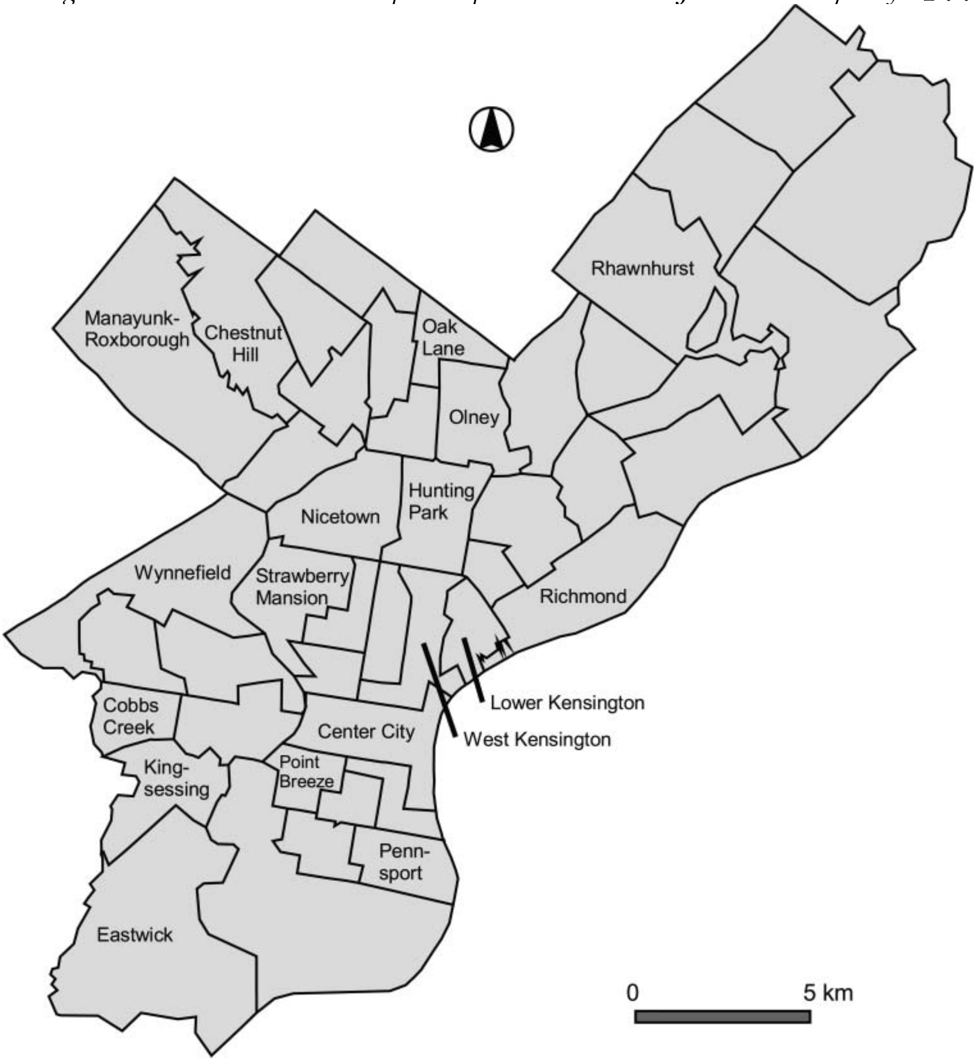

Figure 1 *Map of neighborhood boundaries used the analysis. Names are given for neighborhoods of particular import to this study.*

and was designed to evaluate all programs used by the City of Philadelphia for its delinquent youths. ProDES is case-based, with a seven-year sample of 26,464 cases (10,980 youths) with cases in family court between 1996 and 2003.

ProDES collects data at four points in time: (1) At the point of disposition (the juvenile equivalent of sentencing), data are culled from the youth's record that contains information such as offense history, placement history, needs (e.g., drug use, mental health problems), and family history; (2) At program intake, staff persons are asked to complete a needs assessment and the youth completes a self-report section containing psychometric scales; (3) At discharge, the intake process is repeated and program staff report on the youth's progress in the program; and (4) Six months following program discharge, a follow-up record check is conducted to identify any new petitions (arrests leading to charges) generated in the juvenile or adult court systems, and telephone interviews are conducted with youths, when available, and guardians. Although the sample ranges in age from ten to twenty years old, the majority (69 percent) are between fifteen and seventeen years old. These cases are primarily male (90 percent) and African American (73 percent).

The cases in ProDES were geocoded based on the home address given at the point of disposition listed for the juvenile. We also restricted our analysis to cases that had been in the system at least six months, to examine only those cases that had the possibility of recidivating. Of those cases, we eliminated female cases from the analysis, as the literature suggests that the causes of female juvenile recidivism differ from those of male juvenile recidivism. We also eliminated from our analysis any juvenile who was removed from his residential neighborhood and who attended a residential treatment program. This study thus focuses on the 11,016 remaining cases in ProDES.

Note that a single juvenile might be listed as multiple cases within the database, if the juvenile continues to reoffend after completing a court-ordered program. If a youth does appear more than once in ProDES, it is also possible for that youth to have moved from one neighborhood to another. We acknowledge this as a limitation of our study; however, we note that more than half of the cases in ProDES represent a juvenile who does not appear again in ProDES as another case. Very few juveniles appear in the ProDES database as more than three cases. Nonetheless, we emphasize that this analysis focuses on rates of delinquency and recidivism cases, not individual juveniles.

We consider two outcome variables derived from ProDES. The first is delinquency rate, defined in our study as the ratio of ProDES cases to the total number of juveniles in each neighborhood. The number of juveniles in each neighborhood was derived from the U.S. Census and defined as youth six to nineteen years old. The overall delinquency rate in the study data set is 6.6 percent. Figure 2 shows a choropleth map of delinquency rate by neighborhood. Delinquency rate appears to be highest in a cluster of neighborhoods around Strawberry Mansion, Nicetown, Hunting Park, and West Kensington (an area collectively known as North Philadelphia), as well as in Point Breeze, and Kingsessing. The lowest delinquency rates occur in Manayunk-Roxborough and Chestnut Hill, as well as in the far northeast region of the city.

The second outcome variable is recidivism rate, defined as the ratio of recidivating cases to the total number of delinquent cases in each neighborhood. Recidivating cases are defined here as those for which there is an arrest leading to charges within six months of the completion of a court-ordered program. These charges can range in severity from a felony criminal offense to a probation violation. The recidivism rate over the entire study data set is 23.4 percent. A map of recidivism rate is shown in Figure 3. High recidivism rate appears to be clustered in Kensington, Richmond, and Hunting Park, as well as in Wynnefield and around Pennsport. Low recidivism rate occurs mostly along the far northern tier of the city from Chestnut Hill through Oak Lane to the far northeast region of the city. Descriptive statistics for delinquency rate and recidivism rate, as well as the explanatory variables described later, are provided in Table 1.

Collective Efficacy

Data on collective efficacy were acquired from the Philadelphia Health Management Corporation's (PHMC) 2000 Southeastern Pennsylvania Household Health Survey, an extensive telephone survey of over 10,000 households in southeastern Pennsylvania of residents' perceptions and characteristics indicating collective efficacy and neighborhood functioning. Survey topics include health status, care, and behavior; social capital; safety and violence; hunger and food availability; child care and youth employment, and demographic characteristics. The neighborhood within which each survey respondent resides is made available as a part of the survey data set, allowing for aggregation of the survey data to the neighborhood boundaries used in this study.

We use five collective efficacy variables derived from the survey: participation, neighbor, improvement, belonging, and trust. The participation variable addresses participation in local civic groups, and the neighbor and improvement variables focus on perceptions that neighbors help each other and work together on community projects. Belonging and trust focus on the perceived relationships community

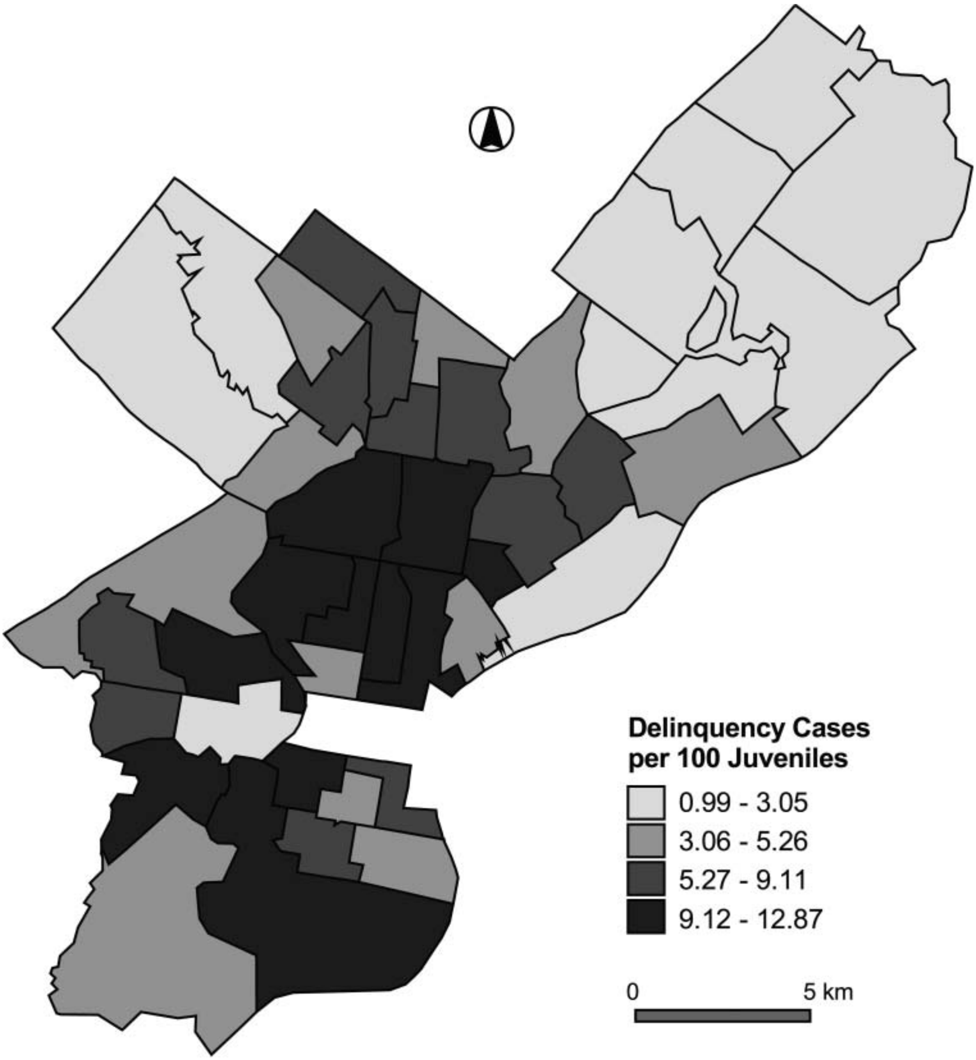

Figure 2 *Quantile-classified choropleth map of delinquency rate by neighborhood.*

members have with their neighborhood and neighbors. The specific survey questions used to generate these variables are given in Table 2. The raw survey data report the response to each of the survey questions, which is typically ordinal or categorical in nature. For the purposes of this study, we calculated the mean response to each question for all the survey respondents within each neighborhood. As an example, Figure 4 shows a choropleth map of the mean trust value by neighborhood. Distrust among neighbors appears to be concentrated in a north–south trending line from West Kensington through Hunting Park and Olney to Oak Lane, as well as along the western edge of the city in Wynnefield, Cobbs Creek, and Eastwick. Interestingly, we make an incidental observation that these neighborhoods appear to be coincident with areas that are either racially diverse (e.g., Southwest Philadelphia) or lie at the boundaries of neighborhoods of different ethnicities. For example, the line of

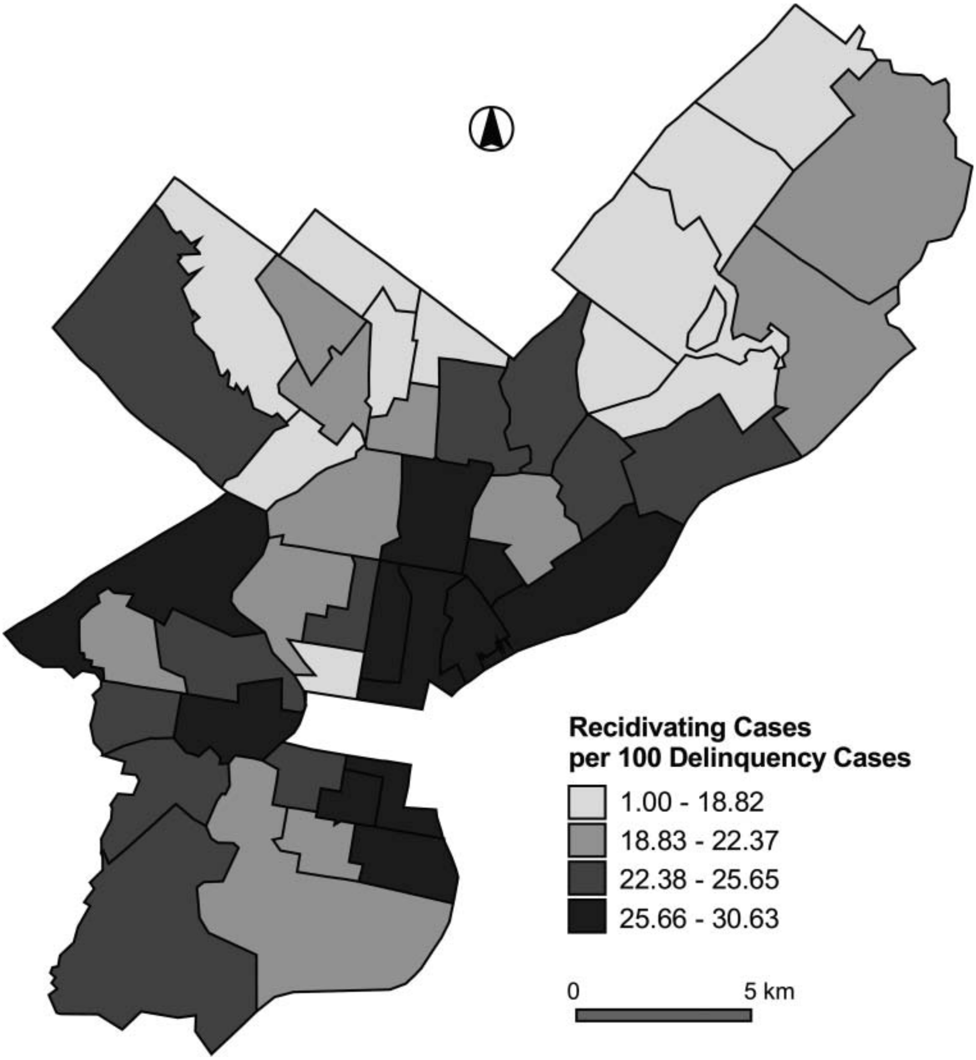

Figure 3 *Quantile-classified choropleth map of recidivism rate by neighborhood.*

neighborhoods running from West Kensington through Oak Lane encompasses predominantly African American (non-Hispanic) areas to the west and white (non-Hispanic) neighborhoods and Hispanic neighborhoods to the east.

Socioeconomic Status

Socioeconomic indicators of poverty and race were derived from the 2000 U.S. Census. These data were acquired at the tract level and aggregated to the neighborhood level—tracts nest perfectly within the neighborhood boundaries used in this study. The following population variables were calculated: percentage receiving public assistance, percentage Hispanic, and percentage African American. Figure 5 shows a neighborhood-level map of percentage receiving public assistance, which appears broadly similar to the spatial pattern of delinquency rate presented in Figure 2. We

Table 1 *Descriptive statistics and correlation of explanatory variables with outcome variables*

Variable	*M*	*SD*	DR Cor	RR Cor
Outcomes (per 100 juveniles/cases)				
Delinquency rate (of juveniles)	6.21	3.49		
Recidivism rate (of delinquent cases)	22.14	4.87		
Collective efficacy				
Participation	0.88	0.34	0.16	0.06
Neighbor	2.04	0.33	−0.10	−0.22
Improvement	1.15	0.18	−0.16	−0.05
Belonging	1.64	0.21	−0.13	−0.11
Trust	1.61	0.23	0.36*	0.02
Socioeconomic status				
Percentage vacant housing	12	7	0.87***	0.47***
Percentage renter occupied	40	13	0.32*	0.18
Percentage Hispanic	8	14	0.35*	0.31*
Percentage African American	46	35	0.64***	0.03
Percentage receiving public assistance	10	6	0.90***	0.48***
Population density (people per km^2)	5,932	2,901	0.37*	0.23
Crime rate (crimes per 100 people)				
Drug offenses	2.37	3.15	0.76***	0.44***
Personal offenses	3.83	2.26	0.94***	0.48***
Weapons offenses	0.30	0.23	0.90***	0.34*
Homicides	0.07	0.06	0.86***	0.31*

Note: Values reported in DR Cor and RR Cor are correlations of explanatory variables with delinquency rate and recidivism rate outcomes, respectively.
*$p < 0.05$.
**$p < 0.01$.
***$p < 0.005$.

also considered two Census household variables indicating neighborhood housing character: percentage vacant housing and percentage renter occupied. We also included a population density variable (people/km^2) as a general indicator of urban concentration, as the city varies from densely populated inner-city neighborhoods with "row home" development (i.e.,

Table 2 *Questions from the 2000 Southeastern Pennsylvania Household Health Survey used to generate the collective efficacy variables*

Variable	Question	Response code
Participation	How many local groups or organizations in your neighborhood do you currently participate in such as social, political, religious, school-related, or athletic organizations?	(# of organizations)
Neighbor	Using the following scale, please rate how likely people in your neighborhood are willing to help their neighbors with routine activities such as picking up their trash cans or helping to shovel snow. Would you say that most people in your neighborhood are always, often, sometimes, rarely, or never willing to help their neighbors?	1 = Always 2 = Often 3 = Sometimes 4 = Rarely 5 = Never
Improvement	Have people in your neighborhood ever worked together to improve the neighborhood? For example, through a neighborhood watch, creating a community garden, building a community playground, or participating in a block party?	1 = Yes 2 = No
Belonging	Please tell me if you strongly agree, agree, disagree, or strongly disagree with the following statement: I feel that I belong and am a part of my neighborhood.	1 = Strongly agree 2 = Agree 3 = Disagree 4 = Strongly disagree
Trust	Please tell me if you strongly agree, agree, disagree, or strongly disagree with the following statement: Most people in my neighborhood can be trusted.	1 = Strongly agree 2 = Agree 3 = Disagree 4 = Strongly disagree

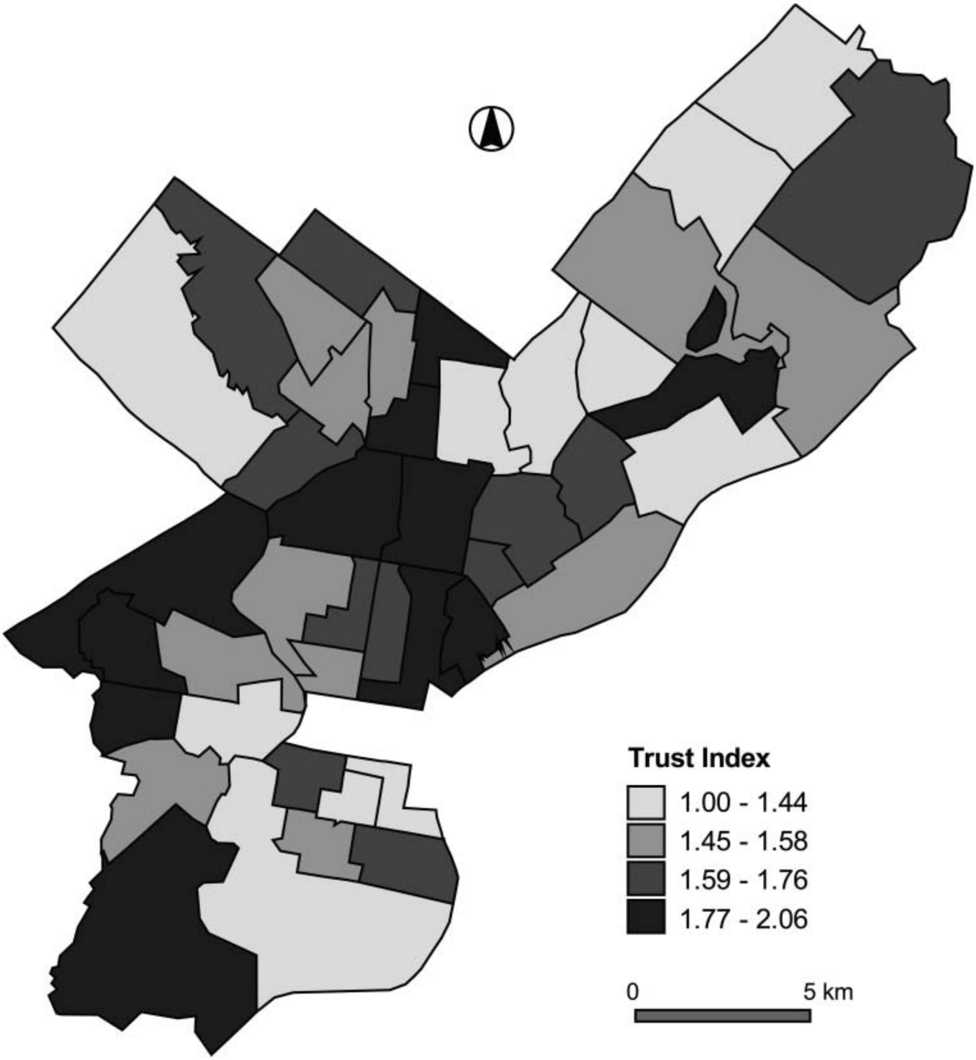

Figure 4 *Quantile-classified choropleth map of the mean trust variable by neighborhood. Note that lower values indicate greater trust of one's neighbors.*

townhouses) to wealthy neighborhoods where single-family homes sit on large parcel lots. Descriptive statistics are provided in Table 1.

Crime

Crime data were acquired from the Philadelphia Police Department. These data included address locations at the street block level for 321,785 incidents of 307 specific types of crimes occurring from 2000 to 2002. Of these incidents, 93 percent were successfully geocoded and grouped into the following crime types: homicide, aggravated assault, robbery, burglary, theft, vehicle theft, weapon, and drug law violations. Aggravated assault and robbery crimes were further aggregated to form a personal offense variable (i.e., violent crimes). In this study, we focused on the most egregious crime types, including personal offenses,

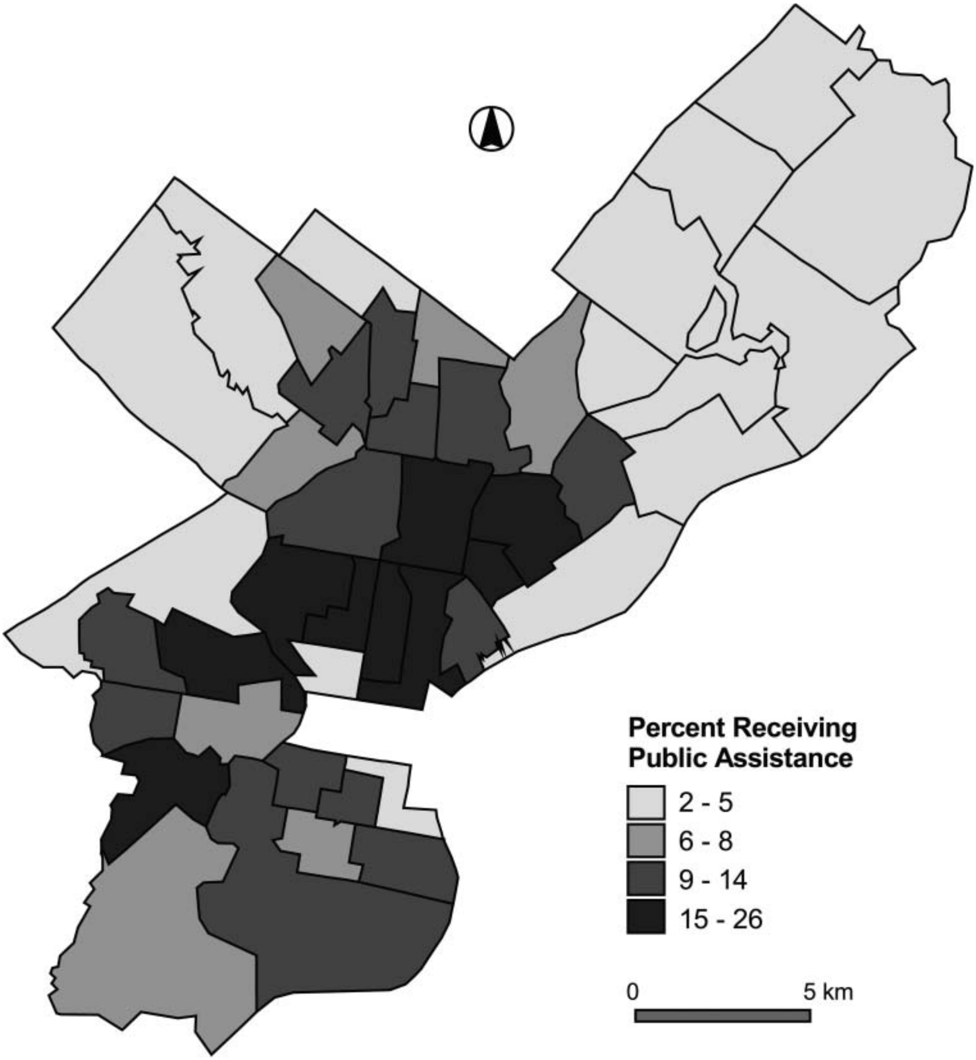

Figure 5 *Quantile-classified choropleth map of the percentage of each neighborhood receiving public assistance.*

homicides, and weapon offenses, as well as drug offenses, as we felt these were most likely to indicate social disorganization. For each of these four crime types, the per capita rate of occurrence was calculated for each neighborhood (Table 1). Figure 6 shows a map of the personal offense rate by neighborhood, which appears to be highly consistent with the spatial patterns of both delinquency rate and percentage receiving public assistance as shown in Figures 2 and 5, respectively.

It is worth noting that the crime data acquired from the police department differ in nature substantially from the juvenile delinquency data captured in ProDES. The police crime data contain arrests for serious offenses, classified as Part 1 offenses under the Uniform Crime Reports code. The juveniles in the ProDES

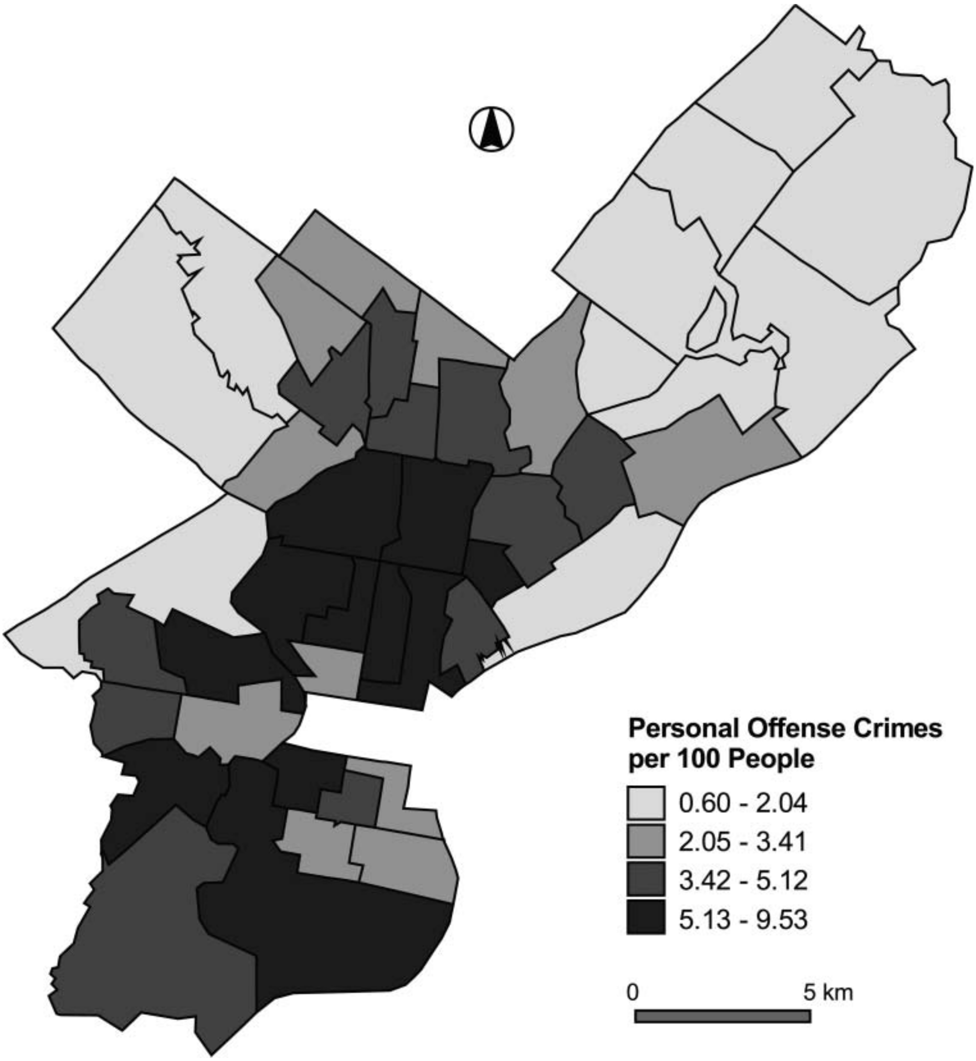

Figure 6 *Quantile-classified choropleth map of personal offense crime rate by neighborhood.*

database typically enter the Family Court system due to minor offenses. Of the youths who commit Part 1 offenses, many are transferred to the adult system and, hence, do not appear in ProDES for processing as adults.

Methods

As a means of exploring unibivariate relationships among variables, the Pearson correlation (r) between each of the explanatory variables with each of the two outcome variables was calculated. We then employ forward-stepwise regression to explore relationships among the explanatory variables in estimating delinquency rate and recidivism rate. For each outcome variable, we run four separate stepwise regressions. Our motivation is to first investigate which explanatory variables are associated with juvenile delinquency and recidivism when each category of explanatory variables is considered in isolation, prior to combining all categories of explanatory variables together. The first stepwise regression includes only the collective efficacy variables as explanators, the second only the socioeconomic status variables, the third only the crime rate variables, and the fourth stepwise regression includes all explanatory variables. We also run a fifth stepwise regression of recidivism rate, in which we allow the juvenile delinquency rate to enter the model as well.

To evaluate the overall quality of the models we employ the coefficient of determination (R^2) as well as the Akaike information criterion (AIC). To assess the normality of the distribution of the residuals we visually evaluated histograms of the distribution of the residuals and used the Jarque–Bera statistic, which tests whether the distribution of the residuals departs significantly from a normal distribution. We also use the well-known Moran's I statistic (with neighbors defined using queen's contiguity) to test for spatial autocorrelation in the residuals, as well as Lagrange multiplier (LM) tests of the spatial lag and error terms. In cases where spatial autocorrelation in the model residuals is present, we employ spatial econometric modeling to account for the spatial effect.

We note that a number of our explanatory variables are collinear, particularly among the following five variables: percentage receiving public assistance, percentage vacant housing, personal offense rate, weapon offense rate, and drug offense rate. In addition, percentage Hispanic is highly correlated with drug offense rate. Although we are aware that some researchers have employed factor analysis to derive single variables that capture the variation in multiple variables, we use individual variables here. Our reasoning is that the crime variables are theoretically distinct from the socioeconomic and infrastructure characteristics of public assistance and vacant housing—it does not make sense to combine these types of variables into a single factor. In addition, different types of crimes are also distinct—drug crimes, for example, tend to cluster in one area of Philadelphia, whereas weapons offenses are more evenly distributed throughout the city.

We take care to develop regression models that are unduly biased by multicollinearity. Although the forward-stepwise regression addresses the issue of collinearity to some extent by only adding explanatory variables to the regression equation whose partial correlation exceeds the 95 percent confidence threshold, we also considered tolerance and variance inflation factor (VIF) diagnostics to address this issue. Due to these diagnostics, we decided to remove percentage vacant housing from the regression.

Results

Results of the correlations among explanatory and outcome variables are reported in Table 1. The collective efficacy variables appear to be largely unrelated to delinquency rate or recidivism rate, with the exception of trust, where increasing neighborhood distrust is associated with increasing delinquency rate, as one would expect. For each of the remaining explanatory variables, the correlation is stronger with delinquency rate than with recidivism rate. All of the socioeconomic indicators are significantly correlated with delinquency rate, with higher rates associated with inner-city, socioeconomically disadvantaged neighborhoods, as one would expect. The percentage vacant housing and percentage receiving public assistance variables exhibit notably high correlations with delinquency rate, as does percentage African American to a lesser extent. High recidivism rate is likewise associated with poverty and housing abandonment. Notably, however, there does not appear to be a relationship between recidivism and percentage African American, percentage renter occupied, or population density. All four crime rate variables are highly and positively correlated with delinquency rate. A similar, although generally weaker, set of correlations can be observed between recidivism rate and each of the crime rate variables. Of the four crime rate variables, personal offense and drug offense rates are more strongly correlated with recidivism rate.

The results of the forward-stepwise regression of delinquency rate are presented in Table 3. Note that all of the models have normally distributed residuals and do not show evidence of problematic collinearity among the explanatory variables. Model 1 shows the results for the stepwise regression where only the neighborhood efficacy variables were used as

Table 3 *Forward-stepwise regression of juvenile delinquency rate*

Explanatory variables	Model 1	Model 2	Model 3	Model 4
Collective efficacy				
Participation		—	—	
Neighbor		—	—	
Improvement	−0.317*	—	—	
Belonging		—	—	
Trust	0.464***	—	—	
Socioeconomic status				
Percentage renter occupied	—		—	
Percentage Hispanic	—		—	
Percentage African American	—	0.326***	—	0.193***
Percentage receiving public assistance	—	0.767***	—	
Population density	—		—	
Crime rate (per 100 people)				
Drug offenses	—	—		
Personal offenses	—	—	0.768***	0.841***
Weapons offenses	—	—		
Homicides	—	—	0.208*	
Constant	0.021	0.006	0.007*	0.004
Adjusted R^2	0.180	0.896	0.899	0.915
Akaike's information criterion	−176.165	−267.175	−268.52	−275.693
Moran's I	3.872***	2.178	0.736	−0.085
Lagrange multiplier (lag)	16.739***	2.290	0.422	0.022
Robust Lagrange multiplier (lag)	6.415*	1.119	0.354	−0.022
Lagrange multiplier (error)	11.694***	2.092	0.069	0.709
Robust Lagrange multiplier (error)	1.370	0.922	0.000	0.709
Jarque–Bera	1.409	5.033	1.457	1.360

Note: $N = 44$. Reported values are standardized coefficients. Dashes (—) indicate that variable category was not entered into the stepwise regression.
*$p < 0.05$.
**$p < 0.01$.
***$p < 0.005$.

explanatory variables. Only the improvement and trust variables were entered into the equation, where increasing distrust of one's neighbors and lower likelihood of working with one's neighbors to improve the neighborhood are associated with higher delinquency rate. Model 2 includes only socioeconomic status variables as indicators and shows that nearly 90 percent of the variation in delinquency rate is explained by percentage African American and percentage receiving public assistance. Increasing percentage African American and percentage receiving public assistance are associated with increasing delinquency rate, with percentage receiving public assistance the more influential explanatory variable.

Model 3 includes only the crime variables. Here, increasing personal offense and homicide rates are associated with increasing delinquency rate, again with nearly 90 percent of the variation in delinquency rate explained. Model 4 includes all the variables, and only percentage African American and personal offense rate are significant. As compared to Models 2 and 3, the goodness of fit is marginally better, the influence of percentage African American is decreased, and the influence of personal offense rate is increased. A Moran's I test (Moran 1948) on the Model 4 residuals indicates no significant spatial autocorrelation at the 0.05 level.

Table 4 presents results for the forward-stepwise regression of recidivism rate, in analogous form to the results presented in Table 3. Again, note that none of the models have residuals that depart significantly from a normal distribution, nor is there evidence of multicollinearity among the explanatory variables. Model 1 indicates that no collective efficacy variables were entered into the regression equation, because none of the variables was significantly correlated with recidivism rate. Model 2 indicates that percentage receiving public assistance rate has a significant positive relationship

Table 4 *Forward-stepwise regression of recidivism rate*

Explanatory variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Collective efficacy					
Participation		—	—		
Neighbor		—	—		
Improvement		—	—		
Belonging		—	—		
Trust		—	—		
Socioeconomic status					
Percentage renter occupied	—		—		
Percentage Hispanic	—		—		
Percentage African American	—		—	−0.324*	−0.440*
Percentage receiving public assistance	—	0.482***	—		
Population density	—		—		
Crime rate					
Drug offenses	—	—			
Personal offenses	—	—	0.484***	0.658***	
Weapons offenses	—	—			
Homicides	—	—			
Juvenile delinquency rate	—	—	—	—	0.727***
Constant		0.185***	0.181***	0.188***	0.186***
Adjusted R^2		0.214	0.216	0.275	0.277
Akaike's information criterion		−149.706	−149.833	−152.368	−152.448
Moran's I		0.237***	0.208**	0.144*	0.112
Lagrange multiplier (lag)		8.470***	7.109**	4.728*	4.257*
Robust Lagrange multiplier (lag)		3.485	3.636	4.270*	5.420*
Lagrange multiplier (error)		5.527*	4.260*	2.043	1.234
Robust Lagrange multiplier (error)		0.525	0.787	1.584	2.397
Jarque–Bera		0.302	0.795	0.188	0.109

Note: $N = 44$. Reported values are standardized coefficients. Dashes (—) indicate that variable category was not entered into the stepwise regression.
*$p < 0.05$.
**$p < 0.01$.
***$p < 0.005$.

with recidivism rate, explaining approximately 19 percent of the variation in the dependent variable. Model 3 indicates a similar relationship of personal offense rate with recidivism rate. Model 4, which considers variables in all categories, includes personal offense rate and percentage African American. Notably, unlike in the analogous model of delinquency rate, percentage African American exhibits a significant negative relationship with recidivism rate. Model 5, which allows delinquency rate to enter the regression equation, basically replaces the personal offense rate variable. This is not surprising given the magnitude of the effect of the personal offense rate variable on delinquency rate (Table 3, Model 4).

The Moran's I statistic applied to the Model 4 residuals indicates the presence of significant spatial autocorrelation at the 0.05 level, and in Model 5 the significance of the Moran's I is 0.068. We speculate that this evidence of spatial dependency in the model residuals derives from spillover effects that occur from the interaction of juveniles from one neighborhood to adjacent neighborhoods. To address the issue of spatial autocorrelation in the model residuals, we employ spatial econometric modeling using maximum likelihood estimation (Anselin 1988). The spatial lag, as opposed to spatial error, form of the spatial econometric model is most appropriate given our hypothesis regarding the spatial spillover effect. Further, our use of the spatial lag model is supported by the LM diagnostics of the spatial lag and error terms for the ordinary least squares (OLS) regression of the recidivism rate (Table 4, Models 4 and 5), which suggest that the spatial lag model is the more appropriate.

We apply two spatial lag models of recidivism rate using the same explanatory variables in Table 4, Models 4 and 5, respectively. The spatial weights matrix is calculated using queen's

Table 5 *Spatial lag regression of recidivism rate*

	Model 1		Model 2	
Explanatory variables	**Coefficient**	***SE***	**Coefficient**	***SE***
Percentage African American	−0.031	0.020	−0.042	0.022
Personal offenses	0.993**	0.330		
Juvenile delinquency rate			0.710**	0.234
Spatial lag term	0.381*	0.167	0.376*	0.166
Constant	0.113**	0.036	0.114**	0.036
R^2	0.396		0.394	
Akaike's information criterion	−154.745		−154.613	

Note: N = 44.
*$p < 0.05$.
**$p < 0.005$.

contiguity. Results of the spatial lag models (Table 5) indicate the spatial lag variable to be significant for both models, and a comparison of the AIC statistics indicates that the overall quality of the spatial lag models is an improvement over the analogous OLS models. This lends credence to the presence of spatial spillover as a causal mechanism, where a neighborhood's recidivism rate is influenced by the recidivism rate of adjacent neighborhoods. Interestingly, the presence of the spatial lag variable in both models causes the percentage African American variable to become not significant at the 0.05 level (although its significance is 0.055 in Model 5).

Discussion and Conclusion

The most striking observation that can be made from the regression results is the difference in predictive power between models of delinquency rate and recidivism rate. The percentage of variation of delinquency rate explained in Table 3 in Models 2, 3, and 4 equals or exceeds 90 percent, demonstrating the extremely strong association of concentrations of juvenile delinquency with neighborhood violent crime and poverty. This is visually apparent in comparing Figures 2, 5, and 6, where high values of all three of these variables tend to colocate in North Philadelphia, Mantua, and Kingsessing.

The regression models of recidivism rate indicate far weaker predictive power as compared to delinquency rate. This is not surprising, given the much stronger spatial clustering exhibited by delinquency rate compared to recidivism rate (Figures 2 and 3, respectively), which suggests that spatially correlated, neighborhood-level explanatory variables are more likely to be detected for delinquency than recidivism. Nonetheless, the most influential predictors of recidivism, as with delinquency, are violent crime and poverty. Recidivism tends to occur more often in impoverished neighborhoods with concentrations of violent crime.

We note that the correlation between violent crime and percentage receiving public assistance is so high that it is indeed impossible to distinguish their effects on delinquency or recidivism rates. In fact, the same can be said to some degree for the combination of these two explanatory variables with percentage vacant housing and, to a lesser extent, the other three crime rate variables. Thus, it perhaps makes the most sense to consider a general crime and poverty mechanism for explaining variation in delinquency and recidivism rates at the neighborhood level.

One of the most interesting findings is that although the presence of crime and poverty appears to increase rates of both delinquency and recidivism, its interaction with race differs substantially between the two outcome variables. Although percentage African American is significant in the Model 4 regressions for both outcomes, its sign is positive for delinquency rate and negative for recidivism rate. A look at the unibivariate correlations presented in Table 1 is enlightening, as percentage African American is significantly and positively correlated with delinquency rate but exhibits no significant relationship with recidivism rate. Percentage

African American is significantly and positively correlated with percentage receiving public assistance (0.41, $p < 0.01$) and personal offense rate (0.54, p, 0.005), so the fact that it is included in Model 4 of delinquency rate (Table 3) suggests that, even accounting for the partially collinear influence of poverty and violent crime, juvenile delinquency rates tend to be higher in African American neighborhoods.

Conversely, however, Model 4 of recidivism rate suggests that, even though recidivism and African Americans tend to colocate in neighborhoods with violent crime and poverty, once the influence of violent crime is accounted for, African American neighborhoods have relatively low recidivism rates. We speculate that low-crime, middle-class African American neighborhoods tend to produce low rates of recidivism, even if delinquency rates remain higher than their white neighborhood counterparts. Or, put another way, of neighborhoods that have high crime rates, non-African American neighborhoods (in Philadelphia, typically white [non-Hispanic] or Hispanic neighborhoods) tend to have higher recidivism rates than African American neighborhoods.

We were admittedly disappointed in the relatively weak relationships observed between the collective efficacy variables and delinquency and recidivism rates. Indeed, none of the collective efficacy variables showed relationships with either of the dependent variables once the influence of the socioeconomic status and crime rate variables were accounted for (as in Model 4 in both Tables 3 and 4). Of all the collective efficacy variables, only the trust variable is significantly correlated with delinquency rate, and none are significantly correlated with recidivism rate. This might be due to the fact that these data are derived from survey questions intended to measure individuals' perceptions and feelings and therefore might reflect more about the specific characteristics of the individual answering the survey than the neighborhood within which the individual resides. To explore these variables more fully, we created choropleth maps of each of the collective efficacy variables (not shown here for reasons of brevity), and we note that, with the exception of the trust variable, they do not appear to follow known patterns of socioeconomic status or other characteristics of the population of which we are aware.

The relatively low values of the goodness-of-fit statistics for models of recidivism rate, compared to delinquency rate, are also notable. This could be due to a variety of factors, such as model misspecification in the form of missing explanatory variables, nonlinear or nonstationary relationships among explanatory and dependent variables, or simply a very noisy dependent variable. Wynnefield, for example, although it is primarily African American (62 percent), is diverse in terms of both race and class, containing both row-home-style housing as well as very large, single-family homes. It is likely that substantial within-neighborhood variation in the explanatory and dependent variables persists. For example, in related investigations of spatial clustering of recidivism rate using kernel density estimation methods, we have found that Wynnefield contains areas of both particularly high, as well as particularly low, recidivism rate. Clearly, such within-unit variation in the dependent variable disturbs accurate parameterization of the regression model.

As a means of exploring the potential causes of relatively low model goodness of fit, we map the residuals of Model 4 of recidivism rate (Figure 7). Interestingly, Figure 7 indicates particular underestimation of recidivism rate for Richmond and overestimation in Rhawnhurst, both working-class, nearly exclusively white (> 90 percent) neighborhoods. The results of the spatial lag models (Table 5), which provide evidence for spatial spillover effects from one neighborhood to its adjacent neighborhoods, might be of some assistance in interpreting the nature of the residuals for these two neighborhoods. Although Richmond has a relatively low personal offense rate and percentage receiving public assistance, it lies adjacent to neighborhoods with high concentrations of crime and poverty. The characteristics of these adjacent neighborhoods might affect the recidivism rate in Richmond through the interaction of individuals across neighborhood boundaries.

We consider this spillover effect to operate through peer contagion, where the deviant behavior of one juvenile is influenced by the behavior of other juveniles with whom they interact. Peer contagion of this nature has been studied in the context of treatment intervention (McCord 2003; Dishion and Dodge 2006) but little research has addressed peer contagion

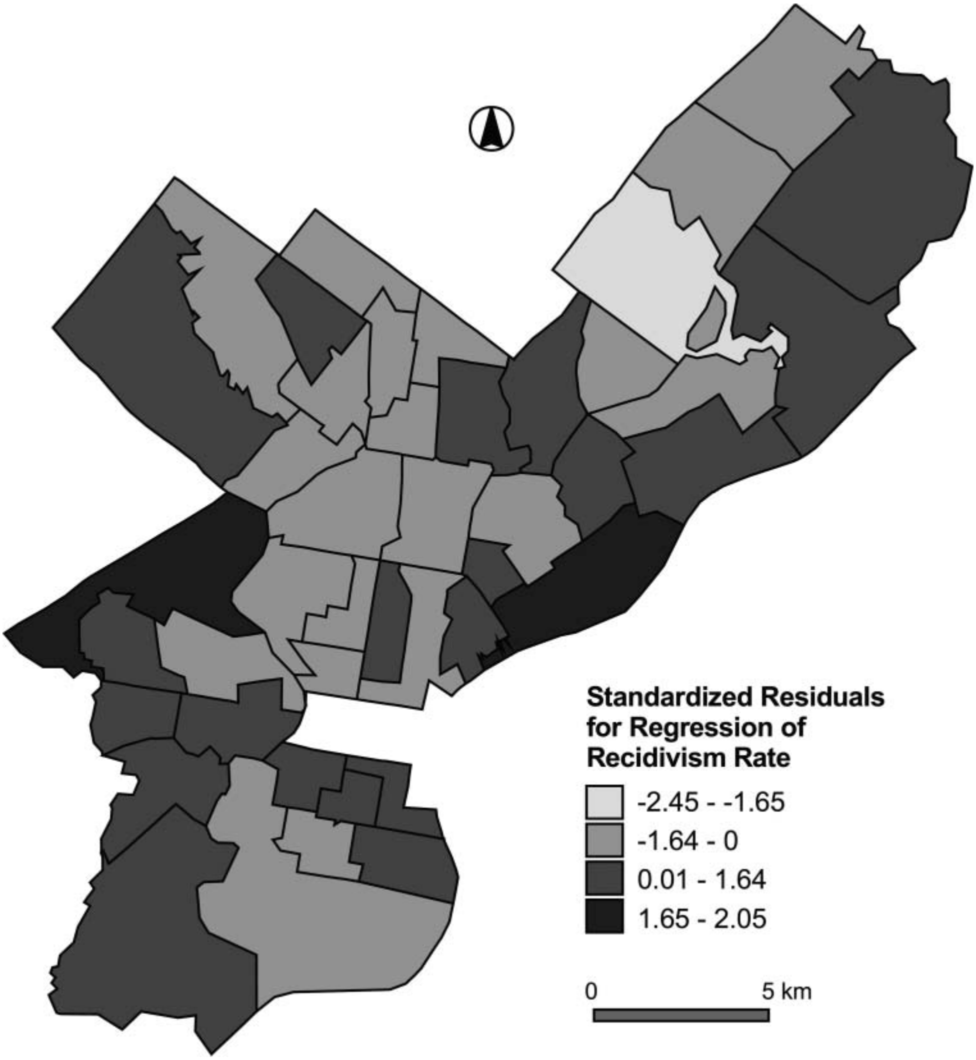

Figure 7 *Choropleth map of standardized residuals for forward-stepwise regression of all variables on recidivism rate (Table 4, Model 4).*

as operating through cross-neighborhood interaction or spatial proximity. Here, we consider that peer contagion across neighborhood boundaries might be captured by the spatial lag model. It is important to note, however, that we have no direct evidence that the spillover effect observed is due to direct contact between peers.

It might also simply be the case that the causes of recidivism differ from neighborhood to neighborhood. For example, although Richmond and Rhawnhurst appear to be similar in socioeconomic character and crime rate, perhaps other nonsocioeconomic or noncriminal components of recidivism are at work in certain neighborhoods. Such spatial nonstationarity would create problems for parameterization of conventional multivariate regression approaches, such as that used in this study, which assumes that relationships among variables hold globally; that is, over the entire data set. It is also possible that the primary causal mechanisms of recidivism are simply not based on collective efficacy, on socioeconomic status, or on crime or that the specific variables employed here do not adequately capture these particular causal mechanisms.

There are other statistical approaches for addressing some of these spatial analytical challenges, including techniques such as hierarchical linear modeling (Jones 1991) and models incorporating spatial nonstationarity (Vucetic and Obradovic 2000; Fotheringham, Brunsdon, and Charlton 2002). We are currently experimenting with a variety of spatial statistics and data mining techniques that we hope will assist in developing improved models of juvenile delinquency and recidivism, both over areas as well as well as at the individual case level. Ultimately, we plan to incorporate neighborhood-level factors with characteristics of the individual case and treatment program to which the case was assigned to better understand the interaction among individual, program, and neighborhood influences on juvenile recidivism. ■

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JEREMY MENNIS is Associate Professor of Geography and Urban Studies at Temple University, Philadelphia, PA 19122. E-mail: jmennis@temple.edu. His recent work focuses on the geographic and social contexts of health and crime behaviors.

PHILIP W. HARRIS is Associate Professor of Criminal Justice at Temple University, Philadelphia, PA 19122. E-mail: phil.harris@temple.edu. His recent work focuses on measuring and predicting recidivism among juvenile offenders.

ZORAN OBRADOVIC is Professor of Computer and Information Sciences and the Director of the Center for Information Science and Technology at Temple University, Philadelphia, PA 19122. E-mail: zoran.obradovic@temple.edu. Web: http://www.ist.temple.edu/~zoran. His research focuses on improving predictive modeling and decision support through data-driven discovery and modeling of hidden patterns in large data sets.

ALAN J. IZENMAN is Professor of Statistics at Temple University, Philadelphia, PA 19122. E-mail: alan@temple.edu. His recent work focuses on multivariate analysis, statistical learning, and data mining, and the application of statistics to law and public policy.

HEIDI E. GRUNWALD is Deputy Director of the Public Health Law Research program at Beasley School of Law, Temple University, Philadelphia, PA 19122. E-mail: grunwald@temple.edu. Recent interests include the use of cross-classified hierarchical linear and propensity score models to examine quasi-experimental data on juvenile recidivism, and youth functional assessment scales.

BRIAN LOCKWOOD is an Assistant Professor in the Department of Criminal Justice at Monmouth University, West Long Branch, NJ 07764. E-mail: brian.lockwood@monmouth.edu. His research interests include the effects of space on juvenile justice outcomes and the influence of spatial structures on urban crime.