

Robberies in Chicago: A Block-Level Analysis of the Influence of Crime Generators, Crime Attractors, and Offender Anchor Points

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Journal of Research in Crime and

Delinquency

48(1) 33-57

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DOI: 10.1177/0022427810384135

<http://jrcd.sagepub.com>



Abstract

The effects of crime generators, crime attractors, and offender anchor points on the distribution of street robberies across the nearly 25,000 census blocks of Chicago are examined. The analysis includes a wide array of activities and facilities that are expected to attract criminals and generate crime. These include a variety of legal and illegal businesses and infrastructural accessibility facilitators. In addition to these crime attractors and generators, the role of the presence of motivated offenders' anchor points, as measured by offenders' residence and gang activity, is assessed. The analysis

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also includes crime attractors, crime generators, and offender anchor points in adjacent census blocks. The findings demonstrate the strength of the effects of crime generators and attractors and offender anchor points on the frequency of street robbery at the census block level.

Keywords

robbery, Chicago, census block, negative binomial, spatial effect

In an ethnographic study on the streets of a deprived Chicago community, St. Jean (2007) tested two major theories of crime and disorder, “collective efficacy” and “broken windows.” He found only limited support for either theory. Observing that even in a deprived area that lacked collective efficacy and social order, many streets and city blocks were relatively crime-free, while others continued to be hot spots of crime, St. Jean asked:

Why is it that, even within the same general high-crime area, crimes such as robbery, drug dealing, and assaults occur much more frequently on some neighborhood blocks than others? (St. Jean 2007:1)

St. Jean’s observation about the local nature of crime concentrations echoes findings from prior research showing that crime hot spots are often not larger than a street segment (Smith, Frazee, and Davison 2000; Weisburd et al. 2004), street corner (McCord and Ratcliffe 2007), or even a single parcel (Kinney et al. 2008) or address (Sherman, Gartin, and Buerger 1989).

Learning from offenders and local residents themselves, St. Jean demonstrated that “pockets of crime” are often located near nodes of cash economies: micro places with specific functions, such as bars, fast-food restaurants, check-cashing centers, and pawn shops, that is, places that bring together, often in large numbers, people who carry cash, some of whom are distracted and vulnerable. In environmental criminology, such places have been labeled *crime attractors* and *crime generators* (Brantingham and Brantingham 1995). Prior studies have documented elevated levels of crime in and around these types of facilities (e.g., see Block and Block 1995; McCord and Ratcliffe 2007; Roncek and Maier 1991). Stucky and Ottensmann (2009) provide an insightful review of the literature on the effects of land use on crime.

This article provides a systematic and large-scale investigation of the extent to which the distribution of crime generators and attractors, in particular street level cash economies, explains the spatial distribution of street robberies, not only in one specific deprived Chicago community but

citywide, across the nearly 25,000 Chicago census blocks. The focus on crime generators and crime attractors is complemented with an exploration of the specific role of *motivated offenders' anchor points* in the geographic distribution of street crime, and with specific attention to spatial spillover effects.

In the remainder of this article, the first section introduces the concepts of crime generators, crime attractors, and offender anchor points. The second section discusses the size of spatial units of analysis, noting that small units are more influenced by their spatial environment than larger ones. The third section describes the data and the statistical models used. Findings are presented in the fourth section and discussed in the fifth section.

Crime Generators, Crime Attractors, and Offender Anchor Points

Crime generators and *crime attractors* are two similar concepts that are used to explain spatial concentrations of criminal activity (Brantingham and Brantingham 1995; Kinney et al. 2008). *Crime generators* are places that are easily accessible to the public. They may become hot spots of crime because the presence of large groups of people creates occasions for crime. Typical examples are shopping precincts, high schools, and public transport stations. Some places provide very specific opportunities and become *crime attractors*. They are places that do not necessarily bring together large groups of people at the same time, but their function makes them well suited for motivated offenders to find attractive and weakly guarded victims or targets. For robbery, crime attractors are likely to be places that have cash economies, that is, places where many transactions are being made, and where the majority of these transactions involve cash, as opposed to payments by credit card or electronic payment systems (Wright and Decker 1997). Most property offenders prefer items that are concealable, removable, available, valuable, enjoyable, and disposable (Clarke 1999; Wellsmith and Burrell 2005), and cash fulfills these requirements best. Payments tend to be cash in small-scale businesses that sell items of limited value. Examples of such businesses are bars, barber and beauty salons, grocery stores, fast-food restaurants, gas stations, and pawn shops.

Some crime attractors are places where the main activities are illegal. *Illegal markets* for gambling, fencing, prostitution, and drug dealing are themselves already hot spots of consensual crimes. They also attract motivated offenders who find the illegal market an ideal hunting ground for theft or armed robbery, because they involve mostly cash transactions and

because many of the participants are vulnerable and will not report victimization to the police.

In addition to crime generators and crime attractors, *offender anchor points* are likely to be relevant for where crime occurs. According to the principle of least effort (Zipf 1949) offenders will—all other things being equal—prefer shorter trips over longer trips. Therefore, a place is more likely to experience crime if it is located nearby offenders' homes.

The “set space” (Tita, Cohen, and Engberg 2005) where gangs hang out can be seen as a special “home-like” anchor point. They are small places such as street corners, empty buildings, or vacant lots where gang members spend a considerable amount of time. Although gangs are not defined in terms of criminal activity, their members are disproportionally involved in crime. Therefore, a place is more likely to experience crime if it is situated in the vicinity of the activity node of a gang.

Spatial Units of Analysis and Spatial Influence

In geographic criminology, it is increasingly recognized that the appropriate spatial unit of analysis needs to be explicitly considered and carefully chosen (Weisburd, Bruinsma, and Bernasco 2009). This decision should not primarily depend on the availability of data or statistical models but must be based on theory: A spatial unit of analysis should match the theoretical perspective that guides the analysis.

The current article addresses the implications of *crime pattern theory*, in particular crime attractors and crime generators: places, locations, sites, or buildings with a function that makes them vulnerable to crime. Crime attractors are without exception much smaller than a neighborhood. Most are even smaller than a football field.

Indeed, most theories that inspire geographical criminology apply to small-scale spatial structures. It is not surprising, therefore, that recent work generally advocates the use of small spatial units of analysis, such as face blocks (Taylor 1997) or street segments (Weisburd et al. 2004) in the U.S. context, and “output areas” (comprising 300 residents on average) in the United Kingdom (Oberwittler and Wikström 2009).

When the analysis is performed on small units of analysis such as census blocks, the size of the relevant environment is relatively large, so that the potential influence of nearby units is comparatively large (Bernasco 2010). Therefore, when analyzing small spatial units, close attention must be paid to the effects of nearby places. The First Law of Geography, which states that “everything is related to everything else, but near things are more

related than distant things” (Tobler 1970:236), warns us not to analytically isolate spatial units from their geographical environment, and the urgency of this warning increases, the smaller the size of the spatial unit of analysis.

Except for an early study in the area (Heitgerd and Bursik 1987), in criminology, the recognition of the importance of spatial interdependence emerged only during the last two decades. Since the turn of the century many studies have addressed the issue of spatial interdependence and have applied statistical methods and techniques to deal with it, either as a potential source of bias or as a substantive hypothesis (Andresen 2006; Baller et al. 2001; Hipp 2007; McCord and Ratcliffe 2007; Mears and Bhati 2006; Messner et al. 1999; Smith et al. 2000).

Proximity of a place to a crime attractor or generator may increase the amount of crime in that place because it is located on the paths that lead toward and from the crime attractor or crime generator. For example, if a subway station attracts passengers, many of these passengers exit to the streets. From the station exit they travel further, often by foot, to their destination. This can be their parked car, a bus stop, their workplace, a store, or a friend’s home. Thus, there will be a strong concentration of transient passengers in the block near the subway station exit, and this concentration will spill over and dilute over adjacent blocks as people start walking toward their destinations.

It is also possible that the presence of a crime attractor or generator in a block increases the amount of crime in that block, but thereby decreases the amount of crime in nearby blocks. Offenders who would otherwise commit crime in the nearby block are being “pulled away” toward the block where the crime attractor or crime generator is located. For example, if a robber moves his “territory” to a nearby area after a new crime attractor emerges in that area, then the crime attractor in the nearby area effectively reduces crime in the robber’s former territory. In the spatial economics literature and marketing literature, these two opposing spatial mechanisms are referred to as the spatial agglomeration and the spatial competition effect (Fotheringham 1985).

Data and Method

The analyses in this article use a large amount of detailed information collected and brought together from various sources. The core consists of information on 75,065 incidents of street robbery recorded by the Chicago Police Department in the years 1996–1998 (an incident may include more than one offender and one or more victim). For this study, street robbery

included all incidents that occurred in an outdoor public location. The data on these incidents include the date and time of the offense and the nearest address to where the robbery was committed. About 98.5% of these addresses were successfully geocoded. Using longitude and latitude, each incident was assigned to one of 24,594 census blocks in the city of Chicago.¹

Crime generators pull criminal activities because they bring together many people at the same time and place. Two infrastructural aspects of census blocks function in particular as accessibility facilitators, namely, (1) whether the block is located along at least one main surface street (rather than only minor streets) and (2) whether there is a public transport station located in the block (Block and Block 1999). In our Chicago data, we coded stops of the El, the Chicago elevated railway system.

To measure robbery crime attractors, for each Chicago census block, counts of various types of retail businesses were obtained from marketing information collected by Claritas (www.claritas.com) on businesses in the city. A subset of nine types of shops and businesses was selected for which the proportion of cash transactions is likely to be high and which had less than 11 employees. They include (1) bars and clubs, (2) restaurants, fast-food outlets and food stands, (3) barber shops and beauty salons, (4) liquor stores, (5) grocery stores, (6) general merchandise shops, (7) gas stations, (8) laundromats, and (9) pawn shops, currency exchange, and check-cashing services. Some other types of small businesses were excluded because we thought they were unlikely to be characterized by a high volume of cash transactions, such as furniture stores and clothing stores. Admittedly, there is some subjectivity included in this selection, an issue we address in the discussion.

To measure more specific crime attractors, the local presence of illegal "vice" markets was geocoded from incident files of the Chicago Police Department of the years 1996-1998 and aggregated to the census block level (see the discussion above for geocoding police recorded incidents). They include (1) drug-related incidents, (2) prostitution-related incidents, and (3) gambling-related incidents. Although some illegal market activities may be pursued indoors and go unnoticed by the public and the police, the number of incidents reflect the amount of street level drug dealing, prostitution solicitation, and gambling in a census block.

The presence of offender anchor points was measured by (1) the amount of gang activity in the block and (2) the number of addresses of arrested robbers residing in the block. Police designated gang crimes were used to estimate gang activity. For each census block, and for each of the eight largest

and most active Chicago gangs, the number of gang-related incidents was counted that took place within the block between the years 1993-1996. An incident is classified as gang-related only if there is positive evidence that gang activity or gang membership is a motive for the incident. Block and Block (1993) and Maxson and Klein (1990) discuss the validity of this classification. Examples of gang-motivated incidents are retaliation, territorial defense, recruitment, internal conflict involving leadership, visually or verbally representing the gang, and street-level distribution of narcotics organized by the gang. Note that gang membership alone does not define an incident as gang-related. The large majority are nonlethal violent offenses. Robberies account for 2.8% of the gang-related incidents. Gang members do commit robberies, but they will only be registered as gang-related if explicitly motivated by gang activities or membership (also see Block and Block 1993).

A separate Chicago Police Department (CPD) file included 18,127 addresses of the residence of robbers residing in Chicago, who were arrested for an incident in the city from 1996 to 1998. This is obviously a subset of all robbers, as not all robberies are reported to the police and not all reported robberies are solved by the police. These addresses were geocoded. Offenders who lived outside the city or whose given address did not match a residential address (using property tax roles) in the city were excluded from geocoding. Given those exclusions all were successfully geocoded. Of all the offenders who gave an address in Chicago, about 95% fit the geocoding criteria.

Following the approach suggested by Bernasco and Luykx (2003), the number of offender addresses per census block was used as a measure of the concentration of offender anchor points (because subsequent robberies committed by the same offender could not be distinguished, they may include multiple occasions of the same person).

Information on the block population was obtained from the U.S. 2000 Census. It includes the total numbers of households, families, and residents in the census block and the racial and ethnic composition of the population. The racial and ethnic composition was used to create both the population percentage African American in the block and the ethnic heterogeneity of the block population. Ethnic heterogeneity was defined using a Herfindahl index calculated as $1 - (A^2 + H^2 + W^2) / (A + H + W + O)^2$ where A , H , W , and O are the numbers residents of African American, Hispanic, White, and Other origin, respectively, that lived in the block. The only variable measured at the aggregated block group level (but used here at the block level) is the percentage of households living below the poverty threshold. The three population variables were used only to characterize the residential

population of the 17,144 (70 percent) of the blocks that had more than 20 residents. Descriptive statistics of the variables used in the analysis are displayed in Table 1.

To estimate spatial effects, spatially lagged versions of all relevant independent variables were constructed using a geographic information system (GIS). First, using the "queens criterion," two census blocks were defined to be adjacent if they shared at least a border or a single point. Next, the spatially lagged version of a variable X is defined as the sum of X in all adjacent cells (but excluding the value of X in the focal cell). For example, if a block has a liquor store and there are two more liquor stores in adjacent blocks, the focal block has one liquor store and its local environment has two liquor stores.

Our data comprise over 75,000 street robberies committed over 1996-1998 across nearly 25,000 blocks in Chicago. On average, each block has just over 3 robberies in total, or 1 per year. The number of robberies (over three years) ranges from 0 to 103.

To model the robbery count, we use the negative binomial model, a generalization of the Poisson model that is more flexible with regard to the relation between the mean and the variance (Osgood 2000). Berk and McDonald (2008) warn that substituting the Poisson² model with the more general negative binomial is only an appropriate solution if the cause of overdispersion is in the random part of the model (in the error term) and not in the systematic part (parameters and independent variables). In particular, they argue that overdispersion may be caused by spatial autocorrelation. Spatial autocorrelation in variable X means that there is a significant positive or negative correlation between the value of X in a census block and the values of X in adjacent census blocks. In a regression modeling context, spatial autocorrelation refers to spatial autocorrelation in the residual, a condition that violates the assumption that the observations are independent.

The inclusion of spatially lagged independent variables, representing potential spillover effects of adjacent blocks, does not imply that residual autocorrelation is absent. To assess residual spatial autocorrelation, we calculated a common spatial autocorrelation measure, Moran's I , which reflects the correlation between the regression residual of a block and the mean residual of adjacent blocks (using the Queens criterion for adjacency, that is, including all blocks that touch the focal block in at least a single point). Moran's I was calculated for Pearson residuals³ after each of the models estimated and reported in Table 3 (below).

We also routinely tested for collinearity problems. Ill-conditioned data, data characterized by near dependencies between the independent variables,

Table 1. Descriptive Statistics of Dependent and Independent Variables

Variable	% > 0	Mean	Standard Deviation	Min	Max	N
Robberies	60	3.05	5.51	0	103	24,594
Total population	77	117.75	153.95	0	9,361	24,594
Small commercial businesses (combined)	22	0.45	1.10	0	20	24,594
Illegal markets (combined)	57	7.01	23.73	0	1,148	24,594
Accessibility facilitators (combined)	26	0.58	1.13	0	16	24,594
Gang activities (incidents)	31	1.21	4.09	0	192	24,594
Number of robbers in population	28	0.74	2.04	0	49	24,594
Bars, clubs	4	0.04	0.21	0	3	24,594
Restaurants, food stands, etc.	9	0.12	0.44	0	9	24,594
Barbers, beauty salons	8	0.11	0.43	0	17	24,594
Liquor stores	2	0.02	0.15	0	3	24,594
Grocers	5	0.05	0.24	0	4	24,594
General merchandise stores	1	0.01	0.14	0	11	24,594
Gas stations	5	0.06	0.26	0	4	24,594
Laundromats	1	0.01	0.10	0	2	24,594
Currency exchange, pawn shops	2	0.03	0.22	0	4	24,594
Drug dealing activities (incidents)	55	6.13	22.39	0	1,146	24,594
Prostitution soliciting (incidents)	12	0.71	5.85	0	265	24,594
Gambling activities (incidents)	9	0.17	0.90	0	33	24,594
Main street along block (yes/no)	25	0.25	.44	0	1	24,594
El station in block (yes/no)	1	0.01	0.07	0	1	24,594
Percentage below poverty (Block group)		17.62	15.09	0	100	17,144
Ethnic heterogeneity (Herfindahl index)		.27	.22	0	.75	17,144
Percentage African American		39.61	44.65	0	100	17,144

Percentage with a Positive Count (at least 1), mean, standard deviation, minimum, and maximum ($N = 24,594$ Chicago Blocks, and $N = 17,144$ Chicago Blocks with a population above 20 residents).

Table 2. Mean Number of Robberies 1996-1998. Comparing Blocks with Nearest Crime Attractors Located in the Block, Located in the Next Block or Located Farther Away

Variable	Frequency	Mean Number of Robberies
Total number of blocks	24,594	3.1
Bars and clubs		
in block	892	5.9
in next block	4,954	4.1
farther away	18,748	2.6
Fast-food restaurants		
in block	2,102	7.4
in next block	8,144	3.9
farther away	14,348	1.9
Barbers and beauty salons		
in block	1,978	7.3
in next block	8,090	4.1
farther away	14,526	1.9
Liquor stores		
in block	518	10.2
in next block	3,473	5.8
farther away	20,603	2.4
Grocery stores		
in block	1,197	8.4
in next block	6,464	4.8
farther away	16,933	2.0
General merchandise stores		
in block	235	11.0
in next block	1,412	6.7
farther away	22,947	2.7
Gas stations		
in block	1,191	5.9
in next block	6,284	3.8
farther away	17,119	2.6
Laundromats		
in block	246	9.2
in next block	1,808	6.1
farther away	22,540	2.7
Pawn shops and check cash services		
in block	511	5.5
in next block	3,591	4.7
farther away	20,492	3.0

(continued)

Table 2 (continued)

Variable	Frequency	Mean Number of Robberies
Drugs incidents		
in block	13,428	5.0
in next block	8,890	0.8
farther away	2,276	0.2
Prostitution incidents		
in block	2,939	7.7
in next block	6,918	3.8
farther away	14,737	1.8
Gambling incidents		
in block	2,259	8.6
in next block	8,132	4.1
farther away	14,303	1.6
Main street		
in block	6,197	4.5
in adjacent block	9,674	3.0
farther away	8,723	2.0
El station		
in block	138	13.4
in adjacent block	954	5.7
farther away	23,502	2.9
Any gang activity		
in block	7,634	6.5
in adjacent block	9,766	2.1
farther away	7,194	0.6
Any residences of arrested robbers		
in block	6,838	6.2
in adjacent block	10,052	2.7
farther away	7,704	0.7

can give rise to collinearity problems whereby the results become unstable under small perturbations of the data. Despite the large size of the data analyzed here ($N = 24,594$), the potential for collinearity is present, especially because some of the models incorporate the independent variables as well as their spatial lags, which tend to be correlated. Collinearity diagnostics include the calculation of variation inflation factors (VIF) as well as the condition number.

The VIF of a variable is defined as $VIF_i = 1/(1 - R_i^2)$, where R_i^2 is the multiple correlation coefficient of variable X_i regressed on the remaining independent variables (Belsley 1991a:27). High VIF values indicate serious multicollinearity problems. A cutoff value of 10 has commonly been

suggested, although the acceptability of higher VIF values under some circumstances has also been defended (O'Brien 2007). For each model, we report both the mean and the highest VIF value of each model.

Another multicollinearity diagnostic is the condition number of the matrix of independent variables, for which values above 30 have been suggested as indicating potentially serious collinearity (Belsley 1991b). The condition number is also reported for each model estimated in Table 3.

Findings

Table 2 explores the relations between the number of robberies and presence of crime attractors, crime generators, and offender anchor points in and near a block. For all variables used to represent crime attractors, crime generators, and offender anchor points, simple dichotomous indicator variables were created. For small commercial business activities, the variable indicates whether at least one of each type of business was located in the block. For illegal markets, it indicates whether at least one incident of drugs dealing, prostitution soliciting, or gambling, respectively, was recorded by the police in the block. Accessibility facilitators are the location of a block along a main street and the presence of an El station. The presence of motivated robbers is indicated by whether the block is the residence of at least one arrested robber, and gang activity was indicated by one or more police-recorded gang-related incidents.

Subsequently, a GIS was used to calculate, for each of the dichotomous variables just described, whether they applied to at least one block that was adjacent to the focal block. A new categorical variable was then created according to which the crime attractor, crime generator, or offender anchor points was either (1) located inside the focal block, no matter whether is was also present in an adjacent block, (2) located in an adjacent block, but not in the focal block, and (3) neither located in the focal block nor in an adjacent block, and thus farther away (see Figure 1 for an illustration).

The findings in Table 2 are simple but provide a clear and consistent conclusion regarding each of the crime generator, crime attractor, and offender anchor point categories—small legal commercial businesses, illegal markets, accessibility facilitators, gang activity, and offender residential concentrations. Blocks that have a crime generator or attractor or offender anchor point inside their boundaries have the highest robbery count. Blocks that do not have a crime generator or attractor or offender anchor point, but are adjacent to a block that has one, have fewer robberies. The lowest numbers of robberies are found in blocks that have no generators or attractors or

Table 3. Negative Binomial Regression Models of Robbery Counts per Block in Chicago 1996-1998. Incidence Rate Ratios. N = 24594/17144 Blocks

Variable	A	B	C	D
In focal block				
Nr. of bars and clubs < 10 employees	1.18***	1.16***	1.15***	1.24***
Nr. of fast-food restaurants < 10 empl.	1.29***	1.19***	1.14***	1.18***
Nr. of barbers and beauty salons < 10 empl.	1.28***	1.17***	1.18***	1.14***
Nr. of liquor stores	1.67***	1.49***	1.50***	1.45***
Nr. of groceries	1.34***	1.26***	1.31***	1.30***
Nr. of general merchandise stores	1.65***	1.40***	1.21**	1.20**
Nr. of gas stations	1.51***	1.41***	1.36***	1.42***
Nr. of laundromats	1.58***	1.34***	1.39***	1.42***
Nr. pawn cheques and cheque-cash services	1.53***	1.46***	1.41***	1.44***
Nr. of drug incidents ($\times 10$)	1.13***	1.05***	1.04***	1.03***
Nr. of prostitution incidents ($\times 10$)	1.28***	1.13***	1.10***	1.09***
Nr. of gambling incidents ($\times 10$)	2.70***	1.75***	1.49***	1.34***
Any main street along block	1.57***	1.32***	1.28***	1.23***
Any El station present	4.22***	4.38***	2.94***	2.78***
Nr. of gang activities ($\times 10$)	1.62***	1.21***	1.13**	1.09**
Nr. of Residences of robbers ($\times 10$)	3.80***	1.86***	1.90***	1.38***
Population ($\times 1,000$)	6.55***	3.15***	2.86***	3.08***
In adjacent blocks				
Nr. of bars and clubs < 10 employees		1.01	1.01	1.07***
Nr. of fast-food restaurants < 10 empl.		1.01	.994	1.03***
Nr. of barbers and beauty salons < 10 empl.		1.06**	1.06***	1.03***

(continued)

Table 3 (continued)

Variable	A	B	C	D
Nr. of liquor stores		1.09***	1.1***	1.06***
Nr. of groceries		.987	1.000	.999
Nr. of general merchandise stores		1.10***	1.10***	1.13***
Nr. of gas stations		1.06***	1.04***	1.1***
Nr. of laundromats		1.17***	1.17***	1.19***
Nr. pawn cheques and cheque-cash services		1.16***	1.14***	1.14***
Nr. of drug incidents ($\times 10$)		1.00	1.00	1.00
Nr. of prostitution incidents ($\times 10$)		1.01*	1.01*	1.01***
Nr. of gambling incidents ($\times 10$)		1.10***	1.07***	.969
Any main street along block		1.25***	1.25***	1.23***
Any EI station present		1.60***	1.30***	1.26***
Nr. of gang activities ($\times 10$)		1.03**	1.04***	.992
Nr. of Residences of robbers ($\times 10$)		1.53***	1.49***	1.18***
Population ($\times 1,000$)		1.12***	1.04*	1.30***
Percentage below poverty level (block group)				1.13***
Percentage African American				1.11***
Ethnic heterogeneity (Herfindahl index)				1.34***
Alpha	1.24***	.94***	.67***	.52***
Mean variance inflation factor (VIF)	1.18	1.46	1.46	1.53
Largest variance inflation factor (VIF)	1.88	3.16	3.32	3.23
Condition number	3.39	8.05	9.11	13.18
Spatial autocorrelation Pearson residual	0.37	0.30	0.27	0.22
N	24,594	24,594	17,144	17,144

*** $p < .001$. ** $p < .01$. * $p < .05$.

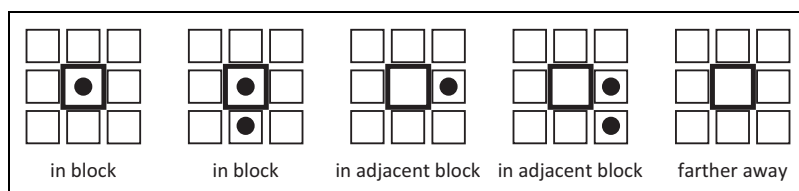


Figure 1. Coding of Location of Crime Attractors as Being “in block,” “in adjacent block,” and “farther away” in Table 2.

offender anchor points and are not adjacent to a block that does. For example, blocks with a barber shop or beauty salon within their boundaries had 7.3 robberies, blocks adjacent to a block with a barber shop or beauty salon had 4.1 robberies, against only 1.9 robberies on average for blocks located farther away from a barber shop or beauty salon. The same ordering holds for all indicators.

Although suggestive, the bivariate relations do not provide sufficient evidence to assess which crime attractors, crime generators, and offender anchor points influence the occurrence of robberies, and which ones are most decisive. The locations of some of the facilities may be correlated. For example, if most barber shops are along main streets and main streets attract robberies, the bivariate relation between robberies and the presence of barber shops may be spurious. Multivariate models alleviate these issues and estimate effects directly and simultaneously.

Therefore, negative binomial models were estimated in which the 24,594 census blocks in Chicago are the units of analysis, the 3-year total number of robberies that occurred in the block is the dependent variable, and the presence and proximity of crime attractors and generators and offender anchor points are the main independent variables.

Model A in Table 3 presents the results of a model that includes as a dependent variable the recorded number of robberies over the years 1996-1998, and as independent variables, the numbers of each of nine types of small legal commercial businesses, the numbers of recorded incidents involving drugs, prostitution, and gambling, the number of police recorded gang activities, the number of residences of robbers, the presence of a main street along the block, and the presence of an El station in the block.

In addition to these crime generator and attractor categories, the population size of the block is included as a generic measure of the “exposure” to robbery risk in the block. Thus, rather than include the population size in the left-hand side of the equation as a denominator of the robbery rate, the

effect of exposure is parameterized in the right-hand side as a separate variable. Note that the exposure to personal crime in an area would normally include both the resident and the transient population (Andresen 2006), those who live in the area and those who visit the area. However, the size of the transient population is not measured directly but is presumed to be incorporated in the effect of the other variables. In other words, crime generators generate crime by drawing an enlarged transient population into the block.

The results of model A displayed in Table 3 support the hypotheses. All crime generators, crime attractors, and offender anchor points increase the number of robberies. For example, adding a liquor store to the block increases the expected number of robberies by 67 percent, and the blocks with an EI station have more than 4 times as many robberies as similar blocks without an EI station.

The bottom of Table 3 presents diagnostic information on the model. The alpha value of 1.24 means that there is considerable overdispersion in the data, indicating the negative binomial model fits the data better than a Poisson model. The mean and maximum VIF and the condition number are all low and indicate the absence of degrading collinearity. The residual autocorrelation of .37 is significant and indicates that the unexplained part of the model, the error term, is spatially clustered. While it is lower than the autocorrelation of .46 in the dependent variable (number of robberies per block), this suggests that some spatially autocorrelated explanatory variables have not been included in the model.

Model B, also presented in Table 3, is identical to model A, but includes spatially lagged variables that indicate the presence of crime generators and crime attractors in adjacent blocks. For example, "Nr. of groceries" in the focal block section indicates the number of groceries in the focal block, while "Nr. of groceries" in the "adjacent blocks" section indicates how many groceries were available in the blocks adjacent to the focal block.

The results of model B demonstrate, first, inclusion of the spatially lagged variables somewhat lowers the estimated effect of the same variable that applies to the focal block (the presence of an EI station being the only exception). For example, the effect of gang activity decreases from 1.62 in model A to 1.21 in model B. This is apparently because gang activity in adjacent blocks is correlated (i.e., spatial autocorrelation in the independent variable) and effects of gang activity in adjacent blocks was attributed to gang activity in the focal block in the interpretation of model A.

Second, all lagged variables have effects similar to those of the original variables although not all are statistically significant. Thus, for example, the

presence of a gas station in the block increases robberies in the block, but so does the presence of a gas station in an adjacent block. Thus, the land uses that attract crime to a block have similar crime-attracting repercussions on adjacent blocks. This is a substantive finding, as potentially some crime attractors may actually “compete” for crime with nearby potential destinations, so that a strong crime attractor in one block actually draws crime away from neighboring blocks. The results of model B show that this is not the case.

Third, the effects of the spatially lagged versions of the variables are consistently smaller than those of the original variable. Thus, as far as the presence of small legal businesses and gang activity is concerned, the presence of a crime generator or attractor in the focal block increases the number of robberies more than does the presence of a crime generator or a crime attractor in an adjacent block.

The diagnostic statistics for this model show that the amount of linear dependency among the independent variables is larger in model B than in model A, which should be expected because all variables tend to be correlated with their spatial lags. Nevertheless, collinearity is not problematic according to standard rules of thumb for VIF (which are all far below 10) and the condition number (which is far below 30). The residual autocorrelation (.30) is lower than in model A, which is to be expected because more variables are included in model B. Taking into account that the model is based on the assumption of zero residual spatial autocorrelation, it is still somewhat high.

The estimates of two additional models are reported in the last two columns of Table 3. Both apply only to the 17,144 census blocks in Chicago, which had more than 20 residents. Restricting the estimation sample to this 70 percent of the total number of blocks allows us to check whether the relations between robbery and the presence of crime attractors, crime generators, and offender anchor points also apply when characteristics are taken into account of the people who live in the block. After all, St. Jean’s ethnographic research was limited to an area with a predominantly poor African American population, while crime pattern theory should be applicable anywhere in principle.

Model C is a copy of model B but applied to the subset of blocks with a population of more than 20. The estimates are very similar to those of model B, except that the effects of population size and spatially lagged population size are weaker in model C (because 30 percent of the blocks at the low end of the population size distribution have been removed) and that the effects of presence of an El station and the spatially lagged presence of an El station

are weaker (EI stations are relatively often situated in nonresidential blocks). All four effects are still positive and significant though. In sum, the main conclusion from the results of model C is that the effects of crime attractors, crime generators, and offender anchor points also hold in residential blocks.

Model D includes a (block group) measure of poverty and the two variables that capture racial and ethnic composition. All three variables are positively related to the number of robberies in the block. The main point to be taken from the results of model D, however, is that the inclusion of population characteristics does not give rise to substantively different conclusions regarding the effects of crime attractors and generators and offender anchor points. All effects that refer to the presence of crime attractors, crime generators, and offender anchor points in the focal block are positive and significant. This holds true also for most of the spatially lagged effects, although between models C and D a few weak effects (lagged bars, lagged restaurants, and lagged gang activities) switch from significance to non-significance or the other way around. Thus, the results of model D demonstrate that the conclusions drawn about effects of crime attractors, crime generators, and offender anchor remain valid when characteristics of the composition of the residential population of the block are taken into account.

Even in model D, which contains no less than 37 independent variables, the diagnostic statistics demonstrate the absence of any degrading collinearity. The VIF and the condition number are well within the limits commonly deemed acceptable. Spatial autocorrelation, however, is still present in the residuals of model D. The inclusion of demographic population variables in this model has further reduced the residual spatial autocorrelation to .22, a value much lower than the unconditional spatial autocorrelation of .46 of the dependent variable, number of robberies in the block, but not negligible.⁴ The existence of nontrivial residual autocorrelation implies that we may underestimate the standard errors of the model coefficients (odds ratios).

Conclusions and Discussion

On the basis of ethnographic research in a deprived Chicago community, St. Jean (2007) demonstrated that even in areas with high crime rates, crimes occur much more frequently in the vicinity of cash economies than in blocks that are completely residential. While St. Jean used the term “ecological disadvantage” to describe the local presence of cash economies,

environmental criminologists have referred to such places as crime attractors and crime generators (Brantingham and Brantingham 1995). The current research has shown that St. Jean's observations not only hold in a single deprived area, but that they apply citywide. It has also demonstrated that in addition to pull factors—the presence and proximity of crime attractors and crime generators—push factors are important as well—the presence and proximity of motivated offenders' anchor points.

The spatial distribution of street robbery was studied across all the nearly 25,000 Chicago census blocks and related to the presence of a wide array of crime generators, crime attractors, and offender anchor points within and nearby these blocks. It was shown that "ecological disadvantage" not only includes the presence of small legal commercial business but also the presence of illegal markets (drugs, prostitution, and gambling), of accessibility facilitators (main streets and public transport hubs), and of the anchor points of motivated offenders. Finally, it was empirically demonstrated that blocks that host crime attractors and generators not only have elevated numbers of robbery themselves but also radiate their elevated crime risk to adjacent blocks. Thus, they do not function as lighting rods that reduce the risk of damage in their immediate environment but instead infect their immediate environment with increased risk.

Similar to St. Jean's original findings, these results seamlessly fit into the environmental criminology perspective that has generally stressed the role of opportunity structures. They provide support for the usefulness of the concepts of crime attractors and crime generators. For crime pattern theory, the inclusion of the locations of offenders' anchor points is specifically relevant because it links aspects of opportunity and general accessibility to the issue of restricted mobility. Blocks located near concentrations of motivated offenders are vulnerable because the geographical range of humans is limited so that motivated offenders generally do not travel far and, thus, are likely to commit crimes near their residences or other anchor points.

While St. Jean was in the position to investigate the indicators of *broken windows* and *collective efficacy* at the level of blocks and street segments in a local community, quantitative city-wide data on levels of social and physical disorder and collective efficacy are not available at the census block level, only at much higher levels of spatial aggregation such as neighborhood clusters (Sampson, Raudenbush, and Earls 1997). Therefore, in this research the explanatory value of "ecological disadvantage" could not be juxtaposed and compared to those of collective efficacy and social and physical disorder.

In contrast to most research on the spatial distribution of crime, in which explanations are sought in the social, demographic, and economic

characteristics of the resident population, our study was mainly concerned with block-to-block variations in land use. The results of models estimated using only the 70 percent of blocks that had a population of more than 20 residents, show that the size of the resident population, the racial and ethnic composition of the block, and the poverty level in the block group do have additional effects beyond those of land use, but also suggest that the effects of crime attractors and generators and offender anchor points are general and apply independently of whether they are located in residential blocks and independently of the specific characteristics of the people who live in the block.

Although the measurement and analysis of census blocks as spatial units of analysis is much more precise, and much better grounded theoretically than the use of aggregates such as block groups or census tracts, it should be noted that a face block, the two sides of a street between two junctions, is an even more natural spatial unit, not only because it is even smaller than a block but also because it is characterized by intervisibility (Smith et al. 2000; Taylor 1997). Furthermore, not all census blocks in Chicago are on a perfect grid. Some of the most important commercial streets are diagonals. Therefore, census blocks along these streets are triangles. Furthermore, census blocks are not only bounded by streets but also by railways and natural barriers such as rivers and Lake Michigan. Future analyses using more detailed geographic features than census block boundaries could provide a deeper understanding of how spatial patterns of robbery are influenced by the urban geography and land uses.

With respect to the statistical modeling of spatial effects, this study has demonstrated the relevance of modeling effects of the spatial environment in situations where the spatial units of analysis are as small as census blocks. Theoretical arguments were put forward to use (negative binomial) regression models with lagged independent variables rather than spatial error or spatial lag regression models.

Other research modeling spatial crime distributions has typically tackled the issue of spatial autocorrelation by using spatial lag or spatial error models (Anselin 1988) and by referring to the associated parameter as indicating spatial "diffusion" or "spillover." Although this spatial diffusion parameter effectively captures remaining residual spatial autocorrelation, in general this procedure as not a constructive modeling approach unless it is very explicitly specified what the "diffusion" or "spillover" process entails. Diffusion, for example, implies a fixed temporal order, and "spillover" assumes a fixed amount that is redistributed, but these characteristics are not implied in the estimation of a spatial autocorrelation parameter.

Spatial lag models assume that the number of robberies in a block has a causal effect on the number of robberies in adjacent blocks, but it is difficult to think of a plausible mechanism that could underlie such an effect. Robbers do not select a place because it is near to the location of other robberies, but because it is near to the target that also attracted other robbers.

The effects of spatially lagged independent variables in our model are much more direct and explicit. They indicate, for example, that the number of robberies in a block is affected by the proximity of a gas station or a grocery store. The nontrivial level of residual spatial autocorrelation that is present in our models is in part a consequence of specifying explicit spatial effects in the form of specified lagged independent variables. The diagnostic value of the result is that it demonstrates that apparently there exist other spatially correlated factors that drive the distribution of robbery incidents at block level but that have not been included in our analyses. Other potentially relevant but unmeasured crime attractors and crime generators include, for example, bus stops, parking places, supermarkets, warehouses, bookstores, clothing stores, and pharmacies. Other potentially relevant block characteristics may include, for example, the signs of physical deterioration and the lack of collective efficacy that St. Jean (2007) investigated.

Acknowledgment

The authors thank the editor of this journal, the guest editors of this special issue, and three anonymous reviewers for helpful comments on a previous draft.

Declaration of Conflicting Interests

The authors declared no conflicts of interest with respect to the authorship and/or publication of this article.

Funding

The geo-coding of the Chicago crime data was funded by the U.S. Department of Justice – National Institute of Justice, the MacArthur Foundation and the Joyce Foundation.

Author's Notes

1. A census block is often thought of as an area that is encompassed by four streets, but this is an oversimplification even in a gridded city like Chicago. Boundaries of census blocks may be railroads or natural barriers (Lake Michigan). Large industrial sites and cemeteries are also census blocks. The size of census blocks ranged from 24 Sq M to 7,756,826 Sq M with a median of 19,680 Sq M. Of

- 24,736 census blocks, 5,867 had no population. There are 142 that had no land; these were excluded from the analyses.
2. Poisson model coefficients were also estimated and compared with those of the negative binomial models presented in Table 3. Only minor differences were found. More specifically, estimates of the Poisson and the negative binomial model were always in the same direction, and did not vary a great deal in magnitude. A few of the spatially lagged variables were just significant in one specification but not in the other.
 3. The Pearson residual is $\frac{y - \hat{y}}{\sqrt{\hat{y}}}$ where \hat{y} is the predicted value and y is the observed value.
 4. To check whether the amount of residual autocorrelation was related to the use of the specific type of residual chosen (the Pearson residual), we verified that other types of residuals (Anscombe residual and Deviance residual, see Pierce and Schafer, 1986) displayed the same amount of residual autocorrelation. We further verified that residual autocorrelation was of approximately the same magnitude when a simple OLS regression model was used instead of the negative binomial regression model. In all cases, residual autocorrelation ranged between .20 and .24.

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