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Go where the money is: modeling street robbers' location choices

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Abstract

This article analyzes how street robbers decide on where to attack their victims. Using data on nearly 13,000 robberies, on the approximately 18,000 offenders involved in these robberies, and on the nearly 25,000 census blocks in the city of Chicago, we utilize the discrete choice framework to assess which criteria motivate the location decisions of street robbers. We demonstrate that they attack near their own homes, on easily accessible blocks, where legal and illegal cash economies are present, and that these effects spill over to adjacent blocks.

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1. Introduction

The public concern about crime in the streets is to a large extent a concern about robbery. The direct property losses from street robbery are usually small. It is rather the unprovoked confrontation with violence that traumatizes victims and their families (Gale and Coupe, 2005) and that generates fear of crime in the general public (Cook, 2009). Fear of crime affects the choices that people make about where to live, work, shop and go out (Cook and Ludwig, 2000). If they can, they will not buy property, accept job offers or go out to places where they fear they might get robbed.

While potential victims avoid exposing themselves to the risk of being robbed by staying away from dangerous places, potential offenders must do the opposite. In this article, we report on a study that aims to improve our understanding of why street robbers are more likely to perpetrate in some places than in others. How do they decide on the appropriate location for finding and attacking their victims? Why do some offenders rob in front of their home, while others rob near the local grocery store, and still others travel many miles to commit a robbery in unknown territory?

We argue that to find suitable victims, motivated robbers must go to places where people are present who are unguarded, vulnerable and nonvigilant, and who carry items that are valuable and disposable. Cash money is by far the best example of such an item, and robbers must thus go where the money is.[1] Examples of such places included in the present analysis are legal businesses like pawn shops, grocery stores and barber shops, but also illegal businesses like hot spots of drug dealing or prostitution. We further assess the extent to which robbers prefer accessible locations along main streets and near public transport hubs, and whether their choices are constrained by where they themselves live and by racial and ethnic barriers to mobility.

Choosing an economic approach to tackle these issues implies that we study the choice of where to commit a robbery as incentive-driven behavior that is comparable to other forms of economic and geographic human behavior, and can fruitfully be subjected to the same type of rigorous economic analysis as more common types of behavior. In other words: the offender's choice of a crime site can be studied in much the same way as the firm's decision of where to open a new store or build new offices (Cheng and Stough, 2006), the angler's choice of a fishing site (Provencher et al., 2002) or the migrant's choice of a place to live (Duncombe et al., 2001). The decision problem is similar, only the choice criteria differ. This claim is substantiated in prior studies on robbers' crime location choices (e.g. Bernasco and Block, 2009), as well as in interviews with active offenders (Wright and Decker, 1997).

In this article, we introduce three major advances over prior work on crime location choice. The first applies to spatial scale. While classic studies on the geography of crime (Shaw and McKay, 1942; Sampson et al., 1997) have used large urban areas as their spatial units of analysis, recent research suggests that often crime concentrations are not larger than a street segment (Smith et al., 2000; Weisburd et al., 2004) or street corner (McCord and Ratcliffe, 2007). To improve our understanding of the fine-grained spatial decisions of street robbers, we zoom in to the level of *census blocks*.

The second advance over prior work in this field of inquiry is our direct test of spatial spillover effects. Census blocks are not independent observational units. Just crossing the street means moving into another block and thus moving from one spatial unit into the next. To assess spatial spillover, we test whether a robber's preference for a census block depends on characteristics of adjacent blocks. Rather than treat spatial effects as nuisance factors to be accounted for in the model disturbance term, they are included in the structural part of the model.

The third innovation is our detailed measurement of a large variety of small-scale cash-dominated economic activities, both legal and illegal, to assess their effect on where robbers choose to attack.

Whereas we previously also investigated spatial spillover effects and used data from the same sources to analyze aggregated robbery counts per census block (Bernasco and Block, 2011), the current analysis improves the prior analysis in two ways. First, it is solidly grounded in random utility maximization (RUM) theory and the discrete choice framework (Ben-Akiva and Lerman, 1994). Second, whereas the prior analysis used aggregated data, the current analysis utilizes disaggregated crime data. These improvements allow us to simultaneously assess the influence of characteristics of offenders and of census blocks, whereas the previous study could only scrutinize the

1 Willie Sutton was a bank robber who allegedly answered the question why he robbed banks by saying "*because that's where the money is*." The quote forms the basis of Sutton's Law, which suggests that any diagnosis should first consider the obvious (Wikipedia entry on 'Willie Sutton', accessed November 30, 2010).

latter. Combining these two types of characteristics, this study yields new findings on how distance and racial/ethnic barriers affect individual crime location choices.

We end this introduction with an overview of what follows. In Section 2, we formulate a theoretical model of robbery location choice, concisely reviewing the relevant literature where necessary. Sections 3 and 4 discuss data and methods, respectively. Section 5 presents the findings and Section 6 is the conclusion and discussion section.

2. Theoretical model

Street robbers use threats or physical force to steal the properties of their victims. They usually attack their victims by surprise and often use a weapon to underline their capability to injure or kill the victim. They wait in ambush for a suitable victim to arrive, or follow a victim until the time and place is suitable for an attack.

The question that inspires our research is not *whether* someone commits a robbery. We take for granted that there exist people who are mentally and physically prepared to act violently and break the law to obtain what they want. The question is *where* they do it, and why they do it there and not somewhere else.

The discrete choice framework describes the behavior of a decision-maker who must choose an alternative from a finite set of alternatives that are mutually exclusive and collectively exhaustive. The aim is to predict—given the attributes of the alternatives and the attributes of the decision-maker—which alternative is chosen.

A theory of choice must address at least four issues (Ben-Akiva and Bierlaire, 1999). It must specify the decision-makers, it must enumerate the elements of the choice set, it must specify relevant attributes of alternatives, and it should make explicit the rules that guide the choice.

2.1. Decision-maker

In the analysis of robbery location choice, it seems obvious that the robber is the agent making the location decision, as it is s/he and nobody else who decides on where to attack the victim. The fact that some street robberies are committed by groups of co-offenders complicates this issue (Bernasco, 2006). Based on victim reports, Cook (2009) estimates 38% of the street robberies to be group offenses. In our own data based on police records of arrested offenders, which are described below, we find 28% of the cleared robberies to involve multiple offenders. In robberies involving multiple offenders, the group must be viewed as the decision-maker. Similar to how multiperson households can be treated as single decision-making agents (e.g. Becker, 1991), we analyze offender groups as single agents. This argument is supported by the finding, to be presented below, that offender groups tend to be highly homogeneous in terms of sex, age, racial and ethnic origin, and residence.

2.2. Choice set

Which are the possible locations where a robber can perpetrate a robbery? Unlike commercial robberies, which can only be perpetrated at places where commercial businesses are located, street robberies can literally be perpetrated anywhere provided a victim is present. This confronts the analyst with the issue of how continuous space can be mapped onto a finite set of discrete spatial units that are meaningful to robbery location choice. Due to the increasing availability of detailed spatial crime data, and in order to minimize the risk of aggregation bias (Openshaw, 1984), contemporary studies on crime and law enforcement generally advocate the measurement of crime at small spatial units of analysis, such as face blocks (Taylor, 1997; Braga et al., 2011) in the USA context, and 'output areas' in the UK (Oberwittler and Wikström, 2009).

We use data that are disaggregated to the level of *census blocks*. In Chicago, with an average surface of 140 m × 140 m (460 ft × 460 ft) and an average population of 118 residents, census blocks are approximately 30 times smaller than census tracts. Zooming in to block level allows us to analyze in a detailed way the location choices of robbers. In 2000 there were 24,594 census blocks in Chicago from which a robber chooses a single one when committing a robbery.

When performing the analysis on units as small as census blocks, spatial spillover effects are plausible (Bernasco, 2010). For example, a retail store that attracts robbers will not only pull robbers to the block where it is located, but also to adjacent blocks that are just across the street and around the corner. A robber may follow a customer from a store in one block to a more isolated place in an adjacent block before s/he attacks, implying that the store in the former block originally attracted the offender that perpetrated the robbery in the latter block. Spatial influence will probably not extend far beyond the length of a single block or maybe two blocks, because generally most potential victims will be vulnerable for the duration of a short walk (to their home, the next store, parking lot, public transport hub). Thus, we suggest the spillover effect will follow a steep distance decay function.

2.3. Relevant attributes of alternatives

On the basis of what criteria do robbers evaluate places as attractive crime locations? Empirical findings from the criminological literature suggest that when robbers select robbery locations they take into account expected *reward*, *effort* and *risk*. Reward is indicated by a preference for places where they can find many potential victims who carry cash and other valuable items. Effort and risk are indicated by a preference for victims who are unguarded and thus can be robbed with relatively little effort and risk of victim resistance, and also by a preference for places that do not require much time and effort to reach, and for places where the risk of being monitored by residents or bystanders and the risk of being arrested by the police is relatively low (Wright and Decker, 1997).

2.3.1. Reward

When robbers choose a location for committing a robbery, they must choose one where they can expect potential victims. Areas with large residential or transient populations are attractive for robberies simply because there is an abundance of potential victims.

The choice of an area for robbery is likely to depend not only on the number of potential victims, but also on the availability of 'good' or 'suitable' victims. In terms of revenues, the best robbery victims possess items that are concealable, removable, available, valuable, enjoyable and disposable (CRAVED) (Clarke, 1999; Wellsmith and Burrell, 2005). Cash is the best example of such an item. Thus, victims that carry large amounts of cash are attractive, and places where such victims are abundant are likely to be attractive places for street robbery.

Victims with cash are best found around cash economies. Therefore, the proximity of check-cashing outlets, automatic teller machines (Holt and Spencer, 2005), pawn shops and other cash-intensive places such as bars and taverns (Roncek and Maier, 1991) makes the surrounding area good hunting grounds for robbers. An ethnographic study of a Chicago police beat found that robbers were attracted primarily to locations with small businesses where cash transactions are the norm (St Jean, 2007). The street robbers interviewed by Wright and Decker (1997) provide many examples of how they are attracted to places where cash flows, including both legal and illegal markets. They found that 60% of the robbers they interviewed 'said that they preyed on individuals who themselves where involved in lawbreaking' (1997, 62). Many preyed on drug dealers or their customers because both dealers and customers are likely to carry either drugs or money, and both items are valuable. Sometimes CRAVED takes on a very literal meaning as the offender actually prefers drugs over money. In a 1996 study of the Drug use Forecasting program (U.S. Department of Justice, 1997), urine tests of arrested robbers in Chicago indicated that around the time of the robbery 49% used cocaine and 82% used any drug. Individuals involved in other 'vices', such as prostitutes and their customers and people involved in illegal gambling, are also likely to be preferred robbery targets because they tend to carry cash.

Students may not be likely to have much cash, but many students visibly carry jewelry, mobile phones, laptops, iPods, electronic gadgets and other valuables that are CRAVED. Students as potential victims are not specifically mentioned in the American ethnographic literature, but crime levels have shown to be elevated in the proximity of high schools (Roncek and LoBosco, 1983; Roncek and Faggiani, 1985) and colleges (Block and Block, 1999), which indicates that pupils may be involved both as victims and as offenders in various types of lawbreaking, including street robberies.

2.3.2. Effort

To minimize effort, robbers searching for a robbery location prefer nearby locations to distant ones. Most individuals have a single home to which they return at the end of the day. Journey to crime research explores the distance between where offenders live and where they commit their offenses. In accordance with the principle of least effort (Zipf, 1949), empirical findings confirm that most robbers commit their offenses within a radius of few miles from their home, and that the frequency of robbery decreases with the distance from their home (Wiles and Costello, 2000; Deakin et al., 2007). Some studies have demonstrated that the proceeds of robbery increase with the distance traveled (Capone and Nichols, 1975; Pettiway, 1982; Van Koppen and Jansen, 1998), which suggests a tradeoff between effort and reward.

Distance is only a partial measure of required effort. Other aspects of accessibility may also make a location attractive to robbers, in particular, whether it is situated along a main street and whether it has quick access to public transport, such as proximity to rapid transit stations (Block and Davis, 1996; Block and Block, 1999). Both attributes have a double function for robbers: they decrease their effort to arrive at and escape from the location, and they also attract potential victims.

2.3.3. Risk

Offenders face the risk of being arrested by the police. The risk of arrest not only depends on police activity, but also on the vigilance of residents and on whether offenders attract their attention. The existence of a racial and ethnic dissimilarities between the offender and the places where they might commit crimes is likely to represent another criterion that influences the spatial decision-making of robbers.

Chicago is among the four most racially segregated cities of the USA (Logan et al., 2004). Most of its citizens, in particular, African Americans, live isolated from other racial and ethnic groups. Segregation may thus function as a 'social barrier' (Rengert, 2004; Reynald et al., 2008) that restrains the mobility of citizens.

Moving into unfamiliar terrain may be uncomfortable for everyone, but for individuals who plan illegal activities it may be outright dangerous. Strangers 'stand out' in places where they do not know the customs and rules, and possibly dress and behave in ways that attract the attention of the local residents. As one of the armed robbers interviewed by Wright and Decker (1997, 75) notes, 'I can go in a black neighborhood, an all-black neighborhood, and I don't stand out, as opposed to me going out there to . . . (a shopping center in the county) where I might stand out'.

Pettiway (1982, 1985) studied the mobility of burglars and robbers in Milwaukee and observed that black ghetto residents overwhelmingly offended inside the ghetto and others outside the ghetto. Using a discrete choice model of robbery location choice in Chicago, Bernasco and Block (2009) demonstrated that when other factors, including distance, are kept constant, African-American, White and Hispanic offenders are all more likely to commit a robbery in a census tract where their own racial or ethnic group forms a majority.

2.4. Decision rule

The fourth element of the theory concerns the decision rule that guides the decision-maker's selection of an alternative from the choice set. This is the domain of random utility theory (McFadden, 1974). The appendix addresses RUM theory and the two specific statistical models that we used for the estimation, the multinomial and the universal logit model.

3. Data

Our analysis utilizes detailed information collected and brought together from various sources. In this section, we discuss characteristics of incidents and offenders, characteristics of census blocks, and the construction of distance measures and spatially lagged census block variables.

3.1. Incidents and offenders

The Chicago Police Department recorded 75,065 street robberies from 1996 through 1998 (for an analysis of total robbery counts per census tract, see Bernasco and Block, 2011). Not all these cases result in an arrest. In fact, in the large majority of cases (82.8%), the offenders escape arrest. The present analyses include the 12,938 cleared cases (17.2%) where at least one person was arrested who was a resident of Chicago.

For this study, street robbery included all incidents that occurred in an outdoor public location. The data on these incidents include the date, the time, the number of arrested offenders involved, and the nearest address to where the robbery was committed. About 98.5% of these addresses were successfully geo-coded. Using longitude and latitude, each incident was assigned to 1 of 24,594 census blocks in the city of Chicago. Our sample excludes the robberies that Chicago residents committed outside the city boundaries. In note 5, we demonstrate that this selection does not result in biased estimates.

Of the 12,938 cleared robberies, 72% were committed by offenders without accomplices, 20% were committed by a pair of co-offenders, 5% were committed by a group of three offenders, 2% by groups of four offenders and 1% by groups of five of more co-offending robbers. Without doubt, situations occurred where some offenders involved in a cleared robbery were arrested but others were not. This necessarily results in an underestimation of the number of offenders involved in a robbery. Because the discrete choice modeling framework assumes a single decision-making agent, and because we do not have information on the decision-making dynamics in pairs and groups of co-offenders, multioffender groups were treated as single decision-making agents.[2] This decision was legitimate given the fact that additional analyses (presented in Supplementary Table S1 of the Supplementary Appendix) showed no statistically significant differences between the parameter estimates of co-offending offenders and those of single offenders.

The data also contains information on the 18,114 offenders who have been arrested for committing these street robberies, including gender, racial and ethnic background, age and residential address at the time of the robbery. These addresses were also geo-coded. Offenders who lived outside the city or whose given address did not match a residential address (using property tax rolls) in the city were excluded from geo-coding. Of all the offenders who gave an address in Chicago ~95% fit the geo-coding criteria (the remaining addresses did not exist or were nonresidential). The demographic composition of the offender sample in terms of age, gender and racial or ethnic background is displayed in Table 1.

Unfortunately, the data did not allow us to identify offenders across multiple robberies. More generally, it did not contain information on prior crimes or past residential addresses of the offenders. Therefore, we must treat robbery location choice as a decision somewhat isolated from the offender's past experiences.

3.2. Census blocks

The data further include detailed information on land use, population and activities in all census blocks in the city of Chicago. In 2000, there were 24,736 census blocks in Chicago. The 142 blocks that had no land were excluded from the analysis. The remaining 24,594 blocks have a median size of 19,680 m^2 (~140 m × 140 m). There are 5867 blocks that have no residential function and thus no residents. These blocks

2 Robbery groups were very homogenous with respect to sex, age and race/ethnicity, and to a lesser extent also residence location. Averaging across all $n(n-1)/2$ offender pairs within groups, 91.4% had the same sex and 94.3% had the same racial/ethnic background (Black, White, or Hispanic). The median absolute age difference was 2 years (mean was 3.2 years), and the median distance between the offenders' homes was 591 m (mean was 2559 m).

Table 1. Offender characteristics

Variable	Frequency (%)
Age group (years)	
7–15	2618 (14.45)
16–20	5458 (30.13)
21–25	3295 (18.19)
26–30	2616 (14.44)
31–35	1765 (9.74)
36–40	1241 (6.85)
41–45	527 (2.91)
46–85	335 (1.85)
unknown	259 (1.43)
Gender	
Male	16,243 (89.67)
Female	1871 (10.33)
Race/Ethnicity	
African-American	14,196 (78.37)
Hispanic	2819 (15.56)
White	993 (5.48)
Asian	45 (0.25)
American Indian/Alaskan Native	13 (0.07)
Other	48 (0.27)
N	18,114 (100)

include parkways, parks, beaches, cemeteries, factories and other areas that may be surrounded by populated blocks. Since robberies can be committed in blocks without a residential function, they are included in the analyses.

A wide range of variables was collected to measure the attractiveness of census blocks for street robbery (see Table 2). To measure the *presence of legal cash economies* and small scale retail activities in the block, we used 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.

To measure the local presence of *illegal cash economies* in the form of drugs, prostitution and gambling transactions, geocoded incident files of the Chicago Police Department of the Years 1996–1998 were aggregated to the census block level. The variables measure numbers of (10) drug-related incidents, which are arrests for soliciting or selling drugs, (11) prostitution-related incidents, which are arrests for soliciting paid sexual services by prostitutes or their customers, and (12) gambling-related incidents, which are arrests for organizing or participating in illegal gambling. All three types of incidents can take place on the streets, in public buildings or private residences.

The *accessibility* of a block is measured by two indicator variables, namely (13) whether the block is located along at least one main street (rather than only minor streets), and (14) whether the block contains a station of the El, the Chicago elevated

Table 2. Descriptive statistics census block variables. Percentage with a positive count (at least 1), mean, SD, minimum and maximum (N = 24,594 Chicago blocks)

Variable	% > 0	Mean	SD	Min	Max
(1) Bars, clubs	4	0.04	0.21	0	3
(2) Restaurants, food stands, etc.	9	0.12	0.44	0	9
(3) Barbers, beauty salons	8	0.11	0.43	0	17
(4) Liquor stores	2	0.02	0.15	0	3
(5) Grocers	5	0.05	0.24	0	4
(6) General merchandise stores	1	0.01	0.14	0	11
(7) Gas stations	5	0.06	0.26	0	4
(8) Laundromats	1	0.01	0.10	0	2
(9) Currency exchange, pawn shops	2	0.03	0.22	0	4
(10) Drug dealing activities (incidents)	55	6.13	22.39	0	1146
(11) Prostitution soliciting (incidents)	12	0.71	5.85	0	265
(12) Gambling activities (incidents)	9	0.17	0.90	0	33
(13) Main streets	25	0.57	1.13	0	16
(14) El stations	1	0.01	0.08	0	2
(15) High schools	0	0.00	0.07	0	1
(16) Total population	77	117.75	153.95	0	9361
(17a) Population < 20	23	0.23	0.42	0	1
(17b) African-American majority	28	0.28	0.45	0	1
(17c) White majority	18	0.18	0.36	0	1
(17d) Hispanic majority	7	0.07	0.26	0	1
(17e) Mixed	26	0.26	0.44	0	1

railway system. Data on (15) the presence of private and public *high schools* in a census block were based on lists compiled by the Chicago Public Schools.

Table 3 presents the correlations between the above 15 variables. Note that most correlations are positive and small to medium in size, indicating a slight tendency for small legal and illegal businesses to be co-located in the same blocks.

Information on block population was obtained from the US 2000 Census. It includes (16) the total number of residents in the census block and the racial and ethnic composition of the population. The population size and the racial and ethnic composition (17) were used to create a five-category classification of each block, i.e. (a) population 20 or less (b) majority African-American, (c) majority White, (d) majority Hispanic and (e) mixed racial and ethnic composition. The majority threshold was defined as 75%.

3.3. Geographic measures

For each offender the Euclidian distance was calculated between their home and the midpoints of each of the 24,594 census blocks. The typical distance decay pattern of the distances between the offender's home and the block where they perpetrated the robbery is displayed in Figure 1.

To measure characteristics of the local environment of a census block, a GIS system was used to define for each block the sets of first- and second-order adjacent blocks.

Table 3. Correlations between numbers of various types of crime attractors in Chicago census blocks, and correlations between crime attractors and first-order (lag1) and second-order (lag2) spatial lags. $N = 24{,}594$ census blocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	lag1	lag2
(1) Drugs incidents	–														0.65	0.57
(2) Prostitution incidents	0.07	–													0.49	0.40
(3) Gambling incidents	0.22	0.04	–												0.27	0.23
(4) Fast-food restaurants	0.05	0.06	0.11	–											0.33	0.29
(5) Grocery stores	0.13	0.05	0.09	0.21	–										0.15	0.15
(6) Bars and clubs	0.02	0.03	0.06	0.17	0.07	–									0.13	0.12
(7) Liquor stores	0.09	0.04	0.08	0.17	0.08	0.09	–								0.04	0.04
(8) Barbers and beauty salons	0.05	0.03	0.08	0.28	0.17	0.13	0.14	–							0.29	0.23
(9) Gas stations	0.02	0.04	0.03	0.09	0.06	0.09	0.06	0.08	–						0.17	0.14
(10) Laundromats	0.04	0.03	0.04	0.12	0.10	0.05	0.06	0.09	0.03	–					0.01	0.03
(11) General merchandise stores	0.02	0.03	0.02	0.17	0.08	0.03	0.06	0.11	0.02	0.04	–				0.13	0.10
(12) Pawn shops/cheque-cash	0.07	0.05	0.07	0.20	0.10	0.08	0.09	0.14	0.04	0.05	0.10	–			0.01	−0.00
(13) Mainstreets	0.02	0.03	0.06	0.15	0.07	0.08	0.06	0.11	0.11	0.05	0.04	0.10	–		0.42	0.35
(14) El stations	0.02	0.00	0.01	0.07	0.02	0.01	0.02	0.03	−0.01	0.00	0.00	0.08	0.02	–	0.09	0.13
(15) Highschools	0.02	0.00	0.00	0.00	−0.01	−0.01	−0.01	0.01	−0.00	−0.01	0.00	0.01	0.02	0.01	0.00	0.01

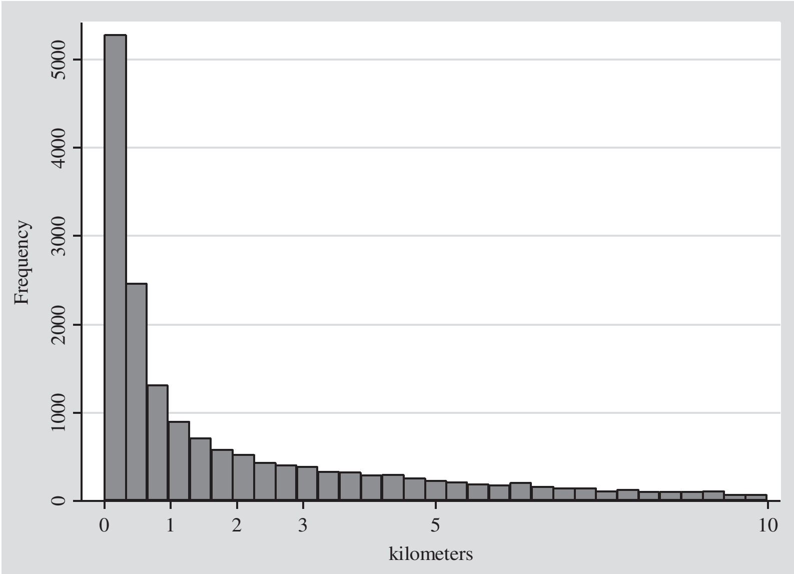

Figure 1. Length of the journey to robbery. $N = 16,709$ crime trips (92%) below 10 km.

Two blocks were defined to be mutually first-order adjacent if they shared a border or a single point. For example, each of the four blocks around an intersection is adjacent to the other three. Two blocks were defined second-order adjacent if they were *not* first-order adjacent and if both were adjacent to a third block.

Subsequently, for each of these 24,594 blocks the values of each of the first 16 variables defined above were summed across the first-order adjacent blocks and across the second-order adjacent blocks. The 2×16 new first- and second-order spatially lagged variables defined potential crime attraction in the local environment of a block, excluding the focal block itself.

4. Methods

This section discusses the statistical implementation of the theory—the multinomial logit model and the universal logit model—including the sampling from alternatives procedure utilized to solve the computational intractability of parameter estimation.

4.1. Correction for sample selection bias

As mentioned in the previous section, the analysis includes only the 17.2% of street robberies that were cleared, i.e. for which at least one offender was arrested who was a Chicago resident. If the likelihood of arrest of Chicago-based offenders varies systematically across census blocks and is correlated with the predictor variables, the analyzed sample is a choice-based sample because robberies in blocks with high arrest probabilities are overrepresented, which may result in biased estimates.

Since the data include the numbers of both cleared and uncleared robberies per block, we were able to correct for this type of sample selection bias. First, using all 75,082 robberies we applied a logit model to regress the likelihood of arrest on all block attributes included in the main model. Results of this logit model (see Supplementary Table S2 of the Supplementary Appendix) showed that there is little evidence in support of the hypothesis that location choice predictors were strongly related to clearance rate: we found significant effects only for population size, high schools and drugs markets, but these variables had extremely little predictive value for clearance rate. Nevertheless, we subsequently used a weighted exogenous sample maximum likelihood (WESML) estimator, in which the cases in the main discrete choice analysis were weighted by the inverse of the predicted probabilities as calculated by the above logit analysis, as suggested in the literature on choice-based samples (Ben-Akiva and Lerman, 1994, 239).

4.2. Case selection and sampling from alternatives

Because the multinomial logit model is directly derived from the specification of the distribution of the disturbance term of the random utility function in Equation (A.2), testing the hypotheses implicated by the theory boils down to estimating the regression coefficients in Equations (A.3) and (A.6). While this is normally a straightforward method, the sheer size of the choice set (i.e. the 24,594 Chicago census blocks) creates a challenge. Because the likelihood function is calculated on every combination of decision-maker and alternative, i.e. on nJ combinations, application to large samples and choices with many alternatives leads to computational problems (Frejinger et al., 2009). Estimating a multinomial logit model on the full data set including all robbers and all census blocks, would involve approximately $25{,}000 \times 13{,}000 = 325$ million decision-maker-by-alternative combinations. Given the iterative nature of maximum likelihood estimation, this task exceeds the limits of most contemporary computer workstations (we used Stata/MP version 11 running on an Intel Xeon 8-core CPU at 2.27 GHz with 12 Gb RAM).

Fortunately, the multinomial logit model can be consistently estimated on a subset of alternatives (McFadden, 1978). Sampling from alternatives is discussed more extensively by Ben-Akiva and Lerman (1994), and has been used in the literature to help estimate the migrant's choice of residential location (Duncombe et al., 2001), the angler's choice of a fishing site (Feather, 1994), the traveler's choice of a route (Frejinger et al., 2009), the worker's choice of employment location (Kim et al., 2008) and the consumer choice of local telephone service (Train et al., 1987).

Knowing that the sampling from alternatives approach yields asymptotically unbiased estimates, we still had to decide on how many alternatives to sample, and which sampling procedure to select. Drawing from simulation research showing how parameter estimate bias depends on the percentage of the sampled alternatives (Nerella and Bhat, 2004), we decided in favor of a conservative approach by selecting a random sample of 6000 census blocks per robbery, which is approximately a quarter of the 24,594 census blocks in Chicago analyzed. Given this sample size, our computer resources allowed us to perform the analysis on a maximum of 6000 robberies of the 12,938 robberies in the total sample.

In sum, a random sample of 6000 robberies was taken, and for each robbery 6000 potential target blocks were selected. One block was the target block actually chosen, and the 5999 others were randomly selected from the 24,594 remaining census blocks. This procedure was followed when estimating both the multinomial logit model (without spatial spillover effects) and the universal logit model (with spatial spillover effects).

Knowing that most offenders commit crimes near their own home, it seems intuitive that 'importance sampling', a procedure that in this case gives more weight to nearby alternatives, would yield more efficient estimates. However, we decided not to use importance sampling because Ben-Akiva and Lerman (1994) argue that despite its intuitive appeal, importance sampling is not more efficient than simple random sampling for estimation purposes.

4.3. Bootstrap estimates

A still more robust set of estimates was obtained with a bootstrapping procedure. Given that our computer memory was strictly limited but not our time, we repeated the analysis just described 25 times, each time selecting a different set of 6000 robberies and for each robbery also selecting a different random sample of 5999 alternative nonchosen blocks. Since this bootstrapping technique yields an additional (between-iteration) variance in the parameter estimates, it provides a more precise estimate of the parameters and a more conservative estimate of their SEs. To combine the results of the 25 iterations, we used Rubin's (1987) formulae for combining the estimates of bootstrapped multiple regression analyses. To sum up, the complete estimation procedure involved the following steps:[3]

1. From the 12,938 robberies, select a random sample of 6000 robberies;
2. For each of these 6000 robberies involving multiple offenders, select a random offender from those involved;[4]
3. For each of the 6000 robberies, select the block where the robbery was actually perpetrated, and add to this a random sample of 5999 blocks of the other 24,593 census blocks;
4. Estimate the multinomial logit and the universal logit model on these 6000 decisions using WESML estimation, and save the estimated coefficients and their robust SEs;
5. Repeat steps 1 through 4 for 25 times, each time taking different random samples and collecting the regression coefficients and their SEs at each step and
6. Using Rubin's rules for combining regression coefficients and SEs from bootstrapped estimation results, for each variable combine the 25 coefficient estimates and the 25 SE estimates into an overall coefficient estimate and an overall SE estimate. These are reported in Table 4. Briefly, Rubin's rules state that the overall *coefficient* is the average coefficient across iterations, while the overall *SE* is the square root of the summed within-iteration and between-iteration variances.

3 The model was also estimated on the full choice set (all 24,594 census blocks) for a random sample of 2000 robberies, yielding estimated coefficients and SEs that were very close to the coefficients and SEs presented in both models of Table 4. This outcome suggests that the estimates are very robust to small variations in the sampling and selection design.

4 In a supplementary analysis, to test for differences between single offenders (72% of the cases) and those who offended in a group (28% of the cases), a dummy variable distinguishing both groups was created, and was interacted with all variables in the models presented in Table 4. None of the interaction effects was statistically significant, demonstrating that single offenders and groups use the same criteria when deciding on where to commit crimes, a finding in line with those of Bernasco (2006).

Table 4. Discrete choice models of robbery target choice in Chicago. WESML estimates from 25 bootstrapped samples of 6000 robberies with random sampling of 6000 from 24,594 blocks

Variables	Multinomial Logit			Spatial Universal Logit		
	β	se(β)	exp(β)	β	se(β)	exp(β)
Focal block						
(1) Bars and clubs	0.186*	0.058	1.204	0.153*	0.057	1.165
(2) Fast-food restaurants	0.228*	0.030	1.256	0.128*	0.031	1.136
(3) Barbers and beauty salons	0.166*	0.022	1.180	0.097*	0.023	1.102
(4) Liquor stores	0.322*	0.070	1.379	0.280*	0.068	1.323
(5) Grocers	0.198*	0.044	1.219	0.137*	0.045	1.146
(6) General merchandise stores	0.195*	0.054	1.216	0.158*	0.059	1.171
(7) Gas stations	0.304*	0.050	1.356	0.273*	0.050	1.314
(8) Laundromats	0.275*	0.113	1.317	0.245	0.112	1.277
(9) Pawn shops/cash services	0.283*	0.049	1.327	0.273*	0.050	1.314
(10) Drug incidents (×10)	0.036*	0.002	1.036	0.030*	0.002	1.031
(11) Prostitution incidents (×10)	0.079*	0.010	1.083	0.054*	0.015	1.055
(12) Illegal gambling inc. (×10)	0.459*	0.067	1.583	0.339*	0.077	1.403
(13) Any main street	0.169*	0.013	1.184	0.084*	0.015	1.088
(14) Any El station	1.231*	0.146	3.425	0.986*	0.152	2.681
(15) Any high school	0.575*	0.168	1.778	0.474*	0.164	1.606
(16) Total population (×1000)	0.530*	0.014	1.700	0.461*	0.019	1.585
(18) −ln(distance) (×km)	1.671*	0.012	5.320	1.667*	0.012	5.298
Adjacent blocks						
(1) Bars and clubs				0.026	0.024	1.026
(2) Fast-food restaurants				0.035*	0.012	1.036
(3) Barbers and beauty salons				0.036*	0.011	1.037
(4) Liquor stores				0.045	0.030	1.046
(5) Grocers				−0.025	0.018	0.975
(6) General merchandise stores				0.098*	0.026	1.103
(7) Gas stations				0.042	0.018	1.043
(8) Laundromats				0.101	0.043	1.106
(9) Pawn shops/cash services				0.101*	0.022	1.107
(10) Drug incidents (×10)				0.003*	0.001	1.003
(11) Prostitution incidents (×10)				0.007	0.006	1.007
(12) Illegal gambling inc. (×10)				−0.001	0.037	0.999
(13) Any main street				0.035*	0.004	1.036
(14) Any El station				0.228*	0.068	1.256
(15) Any high school				0.203*	0.067	1.225
(16) Total population (×1000)				0.185*	0.020	1.204
African-American robbers						
(17b) African-American majority	0.683*	0.068	1.981	0.594*	0.069	1.810
(17c) White majority	0.053	0.122	1.055	−0.076	0.125	0.927
(17d) Hispanic majority	0.142	0.118	1.153	−0.107	0.124	0.899
(17e) Mixed racial/ethnic	0.291*	0.082	1.338	0.128	0.085	1.137
Hispanic robbers						
(17b) African-merican majority	−1.421*	0.344	0.241	−1.495*	0.345	0.224
(17c) White majority	0.212	0.252	1.236	0.072	0.255	1.075
(17d) Hispanic majority	1.341*	0.206	3.823	1.135*	0.206	3.111
(17e) Mixed racial/ethnic	0.809*	0.198	2.246	0.632*	0.200	1.882
White robbers						
(17) African-American majority	−0.668	0.372	0.513	−0.759	0.376	0.468
(17c) White majority	0.650	0.315	1.916	0.569	0.315	1.767
(17d) Hispanic majority	0.669	0.340	1.953	0.450	0.341	1.568
(17e) Mixed racial/ethnic	0.703*	0.280	2.019	0.532	0.282	1.703

Note: *$p < 0.01$ one-sided.

4.4. Collinearity diagnostics

Ill-conditioned data, data characterized by near-dependencies between the independent variables, can give rise to collinearity problems whereby the results become unstable under small pertubations of the data. Despite the large size of the data ($N = 24{,}594$), the potential for collinearity is present, especially because the universal logit model incorporates the census block characteristics as well as their spatial lags, which may be correlated. Calculating both variance inflation factors (VIFs) and condition numbers (Belsley, 1991a, 1991b), we found highly satisfactory values for all variables included in both the multinomial and the universal logit model, and no evidence at all of any degrading collinearity (also see Bernasco and Block, 2011).

5. Findings

Table 4 summarizes the estimation results. The first column lists the explanatory variables. Taking into account that the frequency of journeys-to-crime decreases exponentially with distance, the distance measure was logged to make the result approximately linear in utility (and reversed in order to make its hypothesized effect positive).[5] All variables listed under the heading 'Focal block' are counts or dichotomized counts of businesses or incidents located in the block to which the robbery target choice outcome applies. All variables listed under the heading 'Adjacent blocks' are summed counts or dichotomized summed counts of businesses or incidents located in blocks adjacent to the focal block. The total population of the block is measured in thousands. The specific role of the racial and ethnic composition of the resident population in potential target blocks is modeled conditional on the racial/ethnic background of the offenders: 'African-American robbers', 'White robbers' and 'Hispanic robbers'.

The remaining columns display model outcomes, the leftmost three for the standard multinomial model without spatial spillover effects, and the rightmost three for the universal logit model with spatial spillover effects included. For both models, the first column is the coefficient, the second its SE and the third its exponent. The exponential transformation is included for ease of interpretation: exponentiated β-coefficients represent the factor by which the odds increase that the focal block is chosen for robbery, if the associated variable rises by one unit. For example, according to the outcomes of the multinomial logit model, one more fast-food restaurant on the block means that the odds that the block will be selected for robbery increases by a factor 1.256 (by 25.6%).

5 As discussed in Section 3, robberies outside Chicago are not observed and thus excluded from the analysis. As traveling out of Chicago may result in longer distances, this could create selection bias and may lead to biased distance decay parameters (i.e. the decay seems stronger than it actually is). Because the average distance that offenders live from the city boundaries (4.5 km) is much larger than both the mean and the median residence-robbery distance (3.0 and 1.0 km, respectively), such bias is unlikely. In order to assess whether the distance of the offender's residence from the city boundary is related to the strength of the distance decay parameter, we calculated for every offender the shortest distance to the boundary of Chicago on land (thus excluding the Lake Michigan coastline), and estimated separate distance effects above and below thresholds of 2, 5 and 10 km, respectively. No statistically significant differences above and below the thresholds were found, indicating that distance decay does not depend on where offenders live relative to the city boundary (see Table S3 in the online appendix).

5.1. Multinomial logit model

The multinomial logit model includes only characteristics of the focal block, not those of adjacent blocks. Given the results of other spatial choice models that involve a measure of distance or travel cost (e.g. Duncombe et al., 2001; Bernasco, 2010) it is not surprising that distance from home strongly determines a robber's choice of a target block: a block gets 5.32 times more likely to be selected for robbery for each log-kilometer it is located closer the offender's home (e.g. distances in log-kilometers increase from −3 to 3 in steps of 1 unit as distances in meters progress from 50 to 135 to 365 to 1000 to 2720 to 7390 to 20,100). The finding confirms the results of descriptive studies on the length of the journey-to-crime that emphasize that most offenders do not travel far from their home to commit an offense, and it also confirms the findings from prior studies that utilize distance as an independent variable in a discrete choice model of criminal location choices, including our own (Bernasco and Block, 2009) analysis of Chicago robbery data that used distance measures that were less fine-grained because they were based on census tract centroids.

Under the 'Focal block' heading, the first nine variables measure the presence of small businesses. All nine business types are strongly and positively related to the probability of the focal block being selected for robbery, the multiplicative increase in the odds ranging between 1.18 for number of barber shops and beauty salons to 1.38 for number of liquor stores.

The next three variables represent the amount of illegal market activity over a 3-year period with respect to drugs, prostitution and gambling in the focal block. All three types of activities are significantly and positively related to the likelihood of the block being selected for robbery, which suggests that these illegal activities do attract robbers.

As expected, as the accessibility of the block increases in terms of being situated along main roads and having an El station, so does its probability of being selected for robbery. Furthermore, the presence of an El station has a particularly strong effect: blocks with an El station are 3.43 times more likely to be the location of a robbery than blocks with no El station. A high school in the block increases the odds by a factor 1.78. The presence of a high school in the block could signal the presence of a large potential victim population for robbery, but the students attending the schools may also be offenders for whom the school and the nearby area represent an anchor point that they are familiar with.

The distinction between the three racial and ethnic categories demonstrates an interesting pattern that is generally in line with the hypothesis on racial and ethnic segregation taking on the function of a barrier against criminal mobility. Independently of the other variables (including distance) in the model, African-American robbers are 1.98 times more likely to target a block with a majority (>75%) African-American population than to target a block with no population. They are 1.34 times more likely to target a mixed population (without any majority) block than to target a nonpopulation block. The estimated effects of White or Hispanic majorities (1.15 and 1.06, respectively) are not significantly different from unity.

For Hispanic robbers, the pattern is similar, even more extreme, and with one exception. They are 3.82 times more likely to target a block with a Hispanic majority and 2.25 times more likely to target a mixed population block, than to target a block with no population. They are equally likely to offend in a White majority block as in a zero population block, but they are much less likely to offend in a block with an

African-American majority population (the value of .241 is a negative effect equally strong as a positive effect of $1/0.241 = 4.149$).

White robbers are more likely to choose a block with a White majority, a Hispanic majority or a mixed population, than a block with no population or a block with a African-American majority population. Only the effect of a mixed population block (2.02) is statistically significant, the other two are not.

5.2. Universal logit model

In the universal logit model, the utility derived from choosing a particular block not only depends on attributes of the chosen block, but also on attributes of first-order adjacent blocks, and possibly also on those of higher order adjacent blocks. The estimates of a model including attributes of first-order spatially adjacent blocks are displayed in the last three columns of Table 4.

Comparing estimates between the multinomial and the universal logit model, the effect of distance is virtually identical between models, while the effects of total population, numbers of retail businesses, illegal market incidents and the accessibility measures of the focal block are consistently somewhat weaker in the universal than in the multinomial logit model. All parameters that are significant in the multinomial are also significant in the universal logit model, except for the numbers of laundromats on the block.

That the 'Focal block' variables lose some of their strength in the universal logit model is a direct consequence of the introduction of the spatially lagged adjacent block variables. Since retail businesses, illegal markets and accessibility indicators display positive spatial autocorrelation, these measures are correlated with their spatial lags and thus share variance.

The effects of implementing racial and ethnic contrasts between robbers and their potential target block demonstrate the same patterns of racial and ethnic preference, which are evident in the multinomial logit models. In the universal model, the variables have identical directions and significance levels, although numerically there are some minor shifts.

Generally, the estimates of the spatially lagged adjacent block variables indicate that robbery attraction spills over to adjacent blocks. The effects of the 'spatially lagged' variables, listed in the bottom part of Table 4 under the 'Adjacent blocks' heading, are positive like those of the regular variables, indicating that the same factors that make robbers select a particular block also make them select adjacent blocks. The existence of this 'spatial agglomeration effect' (Fotheringham, 1988) was expected because street robbers must attack close to the businesses that their potential victims are heading to or returning from, as otherwise the victims will have entered their homes, vehicles, public transport or other facilities. They must not necessarily attack on the same block, but neither more than one nor at most two blocks away.

The hypothesis is not self-evident, however, because the opposite phenomenon, spatial competition, is plausible as well. Spatial competition implies that the presence of robbery attractors in adjacent blocks pulls away robbers from the focal block and thus has a negative effect in the probability of robbery in the focal block. In Table 4, without exception, the positive effects of the spatially lagged variables are weaker than the positive effects of their focal block counterparts, which reflects the general geographic reality that near things are more strongly related than distant things.

Subsequently, the universal logit model was extended with the 15 same attributes of second-order spatially adjacent blocks (because of computer memory limitations we used a sample of 4000 instead of 6000 alternatives for this analysis). With one single exception, the estimates (presented in Supplementary Table S4 of the Supplementary Appendix) were nonsignificant. The exception was the total population size, which had significant zero-order [$\exp(\beta) = 1.58$], first-order [$\exp(\beta) = 1.16$], and second-order [$\exp(\beta) = 1.07$] effects, indicating that the population size spillover effect extends somewhat beyond the single block.

6. Discussion

This article outlined a theory of location choice in street robbery, and tested it using data on nearly 13,000 robberies, the approximately 18,000 offenders involved in these robberies, and the nearly 25,000 census blocks in Chicago. The theory asserted that street robbers decide on where to attack by optimizing a combination of the perceived rewards, efforts and risks attached to potential robbery locations. Empirically, it was demonstrated that street robbers living in Chicago are most likely to attack on easily accessible blocks, where legal and illegal cash economies are present. It was also shown that the robbery attracting effects of cash economies and accessibility spill over to adjacent blocks, but not beyond. These findings are in line with what was reported in an earlier study (Bernasco and Block, 2011) that used aggregated data from the same sources. The present analysis represented an improvement because it was explicitly based on RUM theory and it used disaggregated data. In addition to the above-mentioned findings, we demonstrated that blocks become less attractive for committing robbery, the larger the physical distance to the street robber's residence and the larger the social distance to the street robber's racial/ethnic background. For example, Chicago street robbers prefer blocks nearby their homes and blocks that have majority populations matching their own racial or ethnic background.

These answers inspire new questions that could not be answered in the present study because of limitations in the data available. Below we formulate some of these questions and discuss what would be needed to answer them in future inquiries.

6.1. What deters robbers?

Whereas it is crucial to understand what it is that attracts robbers, it is equally important to know what deters them. Possible factors include law enforcement activity (e.g. patrol intensity and investigative efficiency of the police that influence the risk of arrest), victim vigilance (e.g. hired private security personnel around businesses) and criminal competition (e.g. gangs violently dominating the local area). Our data did not contain appropriate localized measures of factors that could potentially deter robbers and force them to choose alternative robbery locations. Although it is important that future work includes such measures, their inclusion in empirical models may not be straightforward. Many of the factors that might deter robbers could actually be *reactions* of law enforcement, potential victims and other offenders to elevated robbery rates. In other words, they might be endogenous and thereby pose challenges to discrete choice model estimation (for a discussion of endogeneity in discrete choice models, see Guevara and Ben-Akiva, 2006).

6.2. Spatial awareness of robbers

Our discrete choice model assumes that robbers in Chicago know the attributes of all 24,594 census blocks. This is a strong assumption, as robbers will typically have detailed knowledge only of the area in the vicinity of their home and around specific activity nodes that are part of their daily routines, legal ones like school, work and leisure and possibly illegal ones like dealing of buying drugs. They will generally have less detailed knowledge of the characteristics of more distant areas of the city. Our findings confirm that proximity to home is among the most important criteria for deciding on a robbery location. This finding could also reflect that robbers are not aware of potential robbery locations located farther away, locations that effectively are not part of their choice set. Limited spatial awareness may also be a reason for why robbers prefer to attack in blocks where the majority of the residents is of their own racial and ethnic origin.

These observations suggest that idiosyncratic offender knowledge plays an important role in crime site selection, as it defines how rewards, efforts and risk are perceived. For example, it has recently been demonstrated that offenders (including robbers) have a tendency to commit offenses in areas of recent past residence (Bernasco, 2010; Bernasco and Kooistra, 2010), suggesting that their knowledge of these areas plays a key role in choosing it for perpetrating a crime. It seems worthwhile to explore if this finding can be generalized to other (former) geographical anchor points of offenders, such as schools, workplaces and homes of families and friends. Future studies will probably require offender-based research, because only offenders themselves can provide detailed information on where they themselves and their friends and family members have lived, on where they went to school and where they worked.

Another question is how target choices are affected by their prior criminal experiences. In the minds of offenders, the locations of prior crimes may also be salient places that could possibly condition subsequent criminal location choices. Recent research on burglary and other crimes demonstrates that in the wake of a crime, the crime risk in the immediate environment is temporarily elevated (Grubesic and Mack, 2008), probably because the same offenders return to their prior crime locations (Bernasco, 2008; Johnson et al., 2009). Unfortunately, our data did now allow us to identify offenders across multiple robberies. Future work could test whether it is generally true that offenders return to locations of prior crimes that were successful, but avoid places where they have been arrested or have otherwise not been successful (in part because most arrested robbers are incarcerated and unable to reoffend for a long time). Such research efforts must use offender-based data, because the police by definition does not identify the perpetrators of unsolved crimes.

6.3. Spatio-temporal choice

When households decide on a new place to live, or firms on a location to build a plant, the rewards, efforts and risks are typically calculated over a time horizon that spans many years, and the precise moment of choice is normally subject to only minor changes in market conditions (e.g. price fluctuations). For other location choices, such as the angler's choice of a fishing site or the offender's choice of a robbery location, the time could be as important as the place. A place attractive for robbery in the morning may be unattractive at night. An entertainment district may be an excellent location in the weekend only. Our inquiry neglects such temporal variations and temporal constraints, and future research could improve our understanding of target selection by replacing spatial choice by spatiotemporal choice, making not only the location but also the time of robbery a subject of choice.

Supplementary data

Supplementary data are available at *Journal of Economic Geography* online.

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Appendix

This appendix describes RUM theory and the multinomial and universal logit models that are derived from the theory and used in the analysis. We follow the notation of Train (2009), and refer to the decision-maker as a 'he' and to the researcher as a 'she'.

A. RUM and multinomial logit

Our decision-making agent is a robber, an individual who is capable and motivated to commit a street robbery. He is labeled n. In our data, $N = 12{,}938$. The alternatives in the choice set are the J possible locations for committing a robbery, from which the robber must choose one. In our data the location is a census block i in the city of Chicago, and $J = 24{,}594$. Robber n expects to obtain a level of utility U_{ni} from perpetrating a robbery at location i if that location is chosen for the robbery. It is assumed that the robber has a perfect discrimination capability, and that he decides in favor of location i if and only if he expects to derive more utility from choosing that location than from choosing any other available location. Thus, if he decides in favor of location i, he must expect to derive less utility from choosing each of the other locations.

$$U_{ni} > U_{nj} \forall j \neq i \tag{A.1}$$

According to RUM theory, the analyst is supposed to have incomplete information, and she only observes the J locations, some attributes of these locations and some attributes of the robber. The sources of the researcher's uncertainty include unobserved attributes of the robber, unobserved attributes of the locations and measurement error. To reflect this uncertainty, utility is modeled as a random variable. The utility that robber n associates with alternative i is given by

$$U_{ni} = V_{ni} + \varepsilon_{ni} \tag{A.2}$$

In Equation (A.2), V_{ni} is the deterministic component of utility, also called *representative utility* or *systematic utility* that captures the knowledge of the analyst. The stochastic or random disturbance term ε_{ni} captures the analyst's uncertainty. For computational convenience, and because any function can be closely approximated by a linear function, representative utility V_{ni} is usually assumed to be linear in the parameters.

$$V_{ni} = \sum_{k=1}^{K} \beta_k X_{kni} \tag{A.3}$$

where K is the number of attributes, X_{kni} is the value of attribute X_k of alternative i for decision-maker n and β_k is a parameter associated with X_k that can be estimated when the actual choices have been observed. From the size, direction and statistical significance of the estimated β parameters, we draw conclusions about the relevant criteria that robbers use when they decide where to commit a robbery.

The probability that robber n chooses location i is the probability that the utility associated with choosing i is greater than the utility associated with any other location in the choice set:

$$P_{ni} = \Pr(U_{ni} > U_{nj} \forall j \neq i) = \Pr(\varepsilon_{nj} - \varepsilon_{ni} < V_{ni} - V_{nj} \forall j \neq i) \tag{A.4}$$

Any specific choice model formulation that is consistent with RUM can be derived from specific assumptions on the joint distribution of the unobserved utility term ε_{ni}.

If the unobserved random utility components ε_{ni} are independent and identically distributed according to an extreme value distribution, the *multinomial logit model* or *conditional logit model* (McFadden, 1974) can be derived, in which the choice probability P_{ni}, the probability that robber n chooses location i, is given by:

$$P_{ni} = \frac{e^{V_{ni}}}{\sum_{j=1}^{J} e^{V_{nj}}} \tag{A.5}$$

B. Universal logit and spillover: effects of attributes of near alternatives

The multinomial logit model is characterized by the independence of irrelevant alternatives (IIAs) property, which is the assumption that the unobserved utility components are uncorrelated across alternatives. This property implies that the utility derived from choosing an alternative depends only on the attributes of the chosen alternative, and not on attributes of other alternatives in the choice set. In many choice situations, in particular those involving spatial choice, this assumption is easily violated. In fact, the spillover notion itself—the notion that the utility derived from choosing a target block depends in part on attributes of the *adjacent* blocks—violates the IIA assumption.

Various alternative models (e.g. nested logit, Generalized Extreme Value logit, mixed logit) that are not saddled with the IIA property have become popular replacements of the multinomial logit model (Train, 2009). They allow the disturbance terms of the utility functions to be correlated across alternatives. While these disturbance terms allow for spatial dependence, they effectively treat it as a nuisance term to be accounted for but not to be tested. To allow tests of substantive hypotheses, spatial effects must however be incorporated into the deterministic part of the model. Some specific spatial models have been proposed, most of them suggesting that the multinomial model be extended with a single specific spatial factor representing centrality, spatial competition or spillover (for usefull overviews, see Boots and Kanaroglou, 1988; Pellegrini and Fotheringham, 2002; Hunt et al., 2004).

A generalization of the logit model that does allow utilities to depend on attributes of multiple other alternatives in the choice set (and thus may violate the IIA assumption) is the *universal* or *mother logit model*. It has been used for testing substitution effects in consumer shopping destination choice (Timmermans et al., 1992) and residential location choice (Miyamoto et al., 2004). In line with our hypothesis that the utility of choosing a census block depends on its own characteristics and those of adjacent census blocks, the representative utility term in this model can be specified as follows

$$V_{ni} = \sum_{k=1}^{K} \beta_k X_{kni} + \sum_{k=1}^{K} \gamma_k \sum_{j=1}^{J} W_{ij} X_{knj} \tag{A.6}$$

in which the second term adds a 'spatially weighted' term to Equation (A.3). Here, W_{ij} is a spatial adjacency matrix of dimensions $J \times J$, such that $W_{ij} = 1$ if block i and block j are adjacent, and $W_{ij} = 0$ if they are not or if $i = j$. Thus, the term $\sum_{j=1}^{J} W_{ij} X_{njk}$ represents the sum of the X_k values in the blocks adjacent to block i, and γ_k is a vector of parameters that represent the spatial spillover effects.

Note that the most general form of the universal logit model allows the utility derived from an alternative to depend on the observed and unobserved characteristics of *all* alternatives in the choice set. Clearly, the generic formulation of the universal logit model implies that 'everything is related to everything else', which is very unrestrictive. Hausman and McFadden (1984) therefore assert that it is 'difficult to give an economic interpretation of this model other than as a flexible approximation to a general functional form' (p. 1219). However, Equation (A.6) is far more restrictive in that it takes Tobler's (1970) First Law of Geography ('Everything is related to everything else, but near things are more related than distant things.') into account and specifies utility to depend on its own characteristics and on those of spatially adjacent alternatives. This implementation has a straightforward economic interpretation in terms of spatial spillover effects.

The dual advantage of applying the universal logit model in this particular application is that it is not saddled with the restrictive IIA property, and that it allows multiple direct tests of the spillover hypothesis (through a test of the γ_k parameters) at the same time. Whereas some other models (e.g. multinomial probit, nested logit, mixed logit) relax the IIA property by allowing flexible error structures in the disturbance part of the model, our application of the universal logit model incorporates spatial effects in the structural part of the model (Miyamoto et al., 2004).