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A Time for a Crime: Temporal Aspects of Repeat Offenders' Crime Location Choices

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Abstract

Objectives: This article examines to what extent repeat offenders' crime location choices are conditional on the timing of the offenses within the week and within the day. Extending crime pattern theory, we argue that offenders acquire time-specific rather than general knowledge of their environment. We hypothesize that offenders are more likely to offend in previously targeted areas at similar than at different days and times. *Methods:* Data on 12,639 offenses committed by 3,666 repeat offenders in the Netherlands are analyzed using discrete spatial choice models. *Results:* Offenders are most likely to offend in areas they already targeted before at similar parts of the week and similar times of the day, especially when the previous offense was committed on exactly the same weekend day or weekday and at the same hour of day. Offenders are less likely to return to previously targeted areas at different times of the week and day, and least likely to offend in areas they

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never targeted before. The effects were stronger for the same than for different types of crime. *Conclusions:* Assessing cyclic time patterns in crime location choice not only enhances our understanding of spatial criminal decision-making, but could also improve predictive policing methods.

Keywords

crime location choice, repeat offenders, crime pattern theory, time-specific awareness space, discrete spatial choice models

Introduction

Criminologists have long been interested in the question where offenders commit crimes. Several decades of research on the geography of crime have shown that initial criminal victimization is associated with a higher risk of being targeted again within a short period of time (e.g., Bowers and Johnson 2005; Farrell, Phillips, and Pease 1995; Morgan 2001). In the repeat victimization literature, these findings are often explained by a tendency of offenders to return to previously targeted areas (Ashton et al. 1998; Bernasco 2008; Everson 2003; Johnson, Summers, and Pease 2009). Two recent studies tested this explanation using an offender perspective (Bernasco, Johnson, and Ruiter 2015; Lammers et al. 2015). Following crime pattern theory (Brantingham and Brantingham 1981; Brantingham and Brantingham 2008), the authors argued that offenders learn where to offend based on their past experiences with criminal risks, rewards, and opportunities. Both studies showed that offenders' prior crime locations indeed strongly influenced their subsequent crime location choices (see Bernasco et al. 2015; Lammers et al. 2015).

Importantly, both crime pattern theory and related empirical research are mainly concerned with offenders' spatial choices of where to commit crime but barely address the *timing* of those choices. Almost all crime location choice studies that used the discrete choice approach (for an overview, see Ruiter 2017) have paid little to no attention to the timing of spatial criminal decision-making within the week or day (for an exception, see Bernasco, Ruiter, and Block 2017). However, why would an offender have knowledge about whether a place is attractive for robbery at night, when he or she previously targeted the area during the day? What does an offender know about the attractiveness of potential burglary targets in an area on Sunday, when he or she only passes through the area on Monday to Friday? Previous spatiotemporal studies outside the crime location choice framework already showed the importance of cyclic time patterns across weeks (e.g., Andresen and Malleson 2015; Johnson, Bowers, and Pease 2012) and over the course of the day (e.g., Haberman and Ratcliffe 2015; Sagovsky and Johnson 2007). In the present study, we argue that offenders' knowledge about the attractiveness of potential target areas applies to specific times and so differs over the seven days of the week and the 24 hours of the day. We thus extend the theoretical and empirical models of Lammers et al. (2015) and Bernasco et al. (2015) by investigating to what extent the timing of previous and subsequent offenses within the week and within the day influences the chance an offender returns to a previously targeted area.

This study contributes to the geography of crime research in three ways. First, we extend Brantingham and Brantingham's (1981; 2008) crime pattern theory by arguing that offender awareness spaces are not static over the week or day but rather *time-specific*. Ignoring temporal variations in offenders' spatial knowledge, previous research implicitly assumed that offenders could commit offenses at any time and day in all possible places within their awareness space. However, awareness spaces in crime pattern theory should be conceptualized as time-specific instead of time-invariant. Second, in contrast to repeat victimization studies, the present study addresses temporal aspects of criminal target selection within the week and day from *an offender's perspective*, thus trying to understand where offenses are committed by looking at those who are ultimately responsible for deciding where and when crime occurs. The only study so far that examined offenders' target location choices for different time intervals (Bernasco et al. 2017) did not take offenders' crime histories into account, let alone compare the time and place of multiple offenses committed by the same offenders. Third, by comparing the *crime types* of previous and subsequent offenses, we also provide more insight into the influence of more general versus crime type–specific knowledge on the decision to target a particular area at a certain day and time. Most previous crime location choice studies only looked at one offense per offender, often also of a specific type (for an overview, see Ruiter 2017), without taking into account that offenders actually might have a history of offenses of similar or different types which influences their subsequent decision-making. We examine the timing of offenders' crime location choices using offenses with a clear geographic location, such as robbery, burglary, theft, and assault.

Theoretical Framework

Answering the question to what extent repeat offenders' crime location choices are time-specific requires research aimed at understanding offenders' spatial criminal decision-making. Two theoretical perspectives are dominant in the crime location choice literature (see Bernasco and Ruiter 2014; Ruiter 2017): the rational choice perspective and crime pattern theory. According to the rational choice perspective, offenders are goal-oriented decision-makers who evaluate the expected costs (e.g., risk of apprehension, obstacles to reach a target) and benefits (e.g., material and symbolic rewards) of potential target areas and choose the target area that is believed to bring them closest to their goals (Bernasco, Block, and Ruiter 2013; Clarke and Cornish 1985). Crime pattern theory also stresses that offenders' crime location searches are far from random. The theory asserts that everyone develops a so-called *awareness space*, which consists of major routine activity nodes, like the home, work, leisure activity locations, and the travel paths that connect them (Brantingham and Brantingham 1981). According to crime pattern theory's geometry of crime, offenders would commit crimes at locations where the distribution of attractive opportunities for crime overlaps with their personal awareness spaces because they have limited knowledge of locations and the potential risks and rewards involved outside these mental boundaries (Brantingham and Brantingham 2008). Bernasco (2010) conceptualized the awareness space more dynamically by not only including areas around contemporaneous activity nodes and the travel paths between them but also those that used to be part of one's activity space in the recent past. He showed that offenders are indeed more likely to commit crimes in areas where they used to live than in comparable areas in which they had never lived.

In the repeat victimization literature, it has often been suggested that victims of crime have an increased risk of being victimized again because offenders would return to the same targets (e.g., Ashton et al. 1998; Bernasco 2008; Everson 2003; Johnson et al. 2009). In line with crime pattern theory, it is argued that offenders' experiences during previous offenses provide them with valuable information about the attractiveness of the target area, which is used in future criminal decision-making (Bernasco et al. 2015; Lammers et al. 2015). Examples include the accessibility of a particular target area, the existence of possible escape routes, and the absence or presence of potential guardians. In all crime location choice studies so far, it has implicitly been assumed that any spatial knowledge acquired would be useful for committing offenses irrespective of their timing. However, when offenders learn about criminal opportunities from previous offenses, their knowledge about the attractiveness of previous target areas might not apply equally to all situations. As the potential risks and rewards involved during the week might be quite different from those during the weekend, offenders' knowledge about the spatial environment that stems from a previous crime event might not be directly related to what the situation is like at an entirely different part of the week. Moreover, why would an offender have knowledge about whether a place is attractive for crime at night, when he or she has previously only targeted the area during the day?

To incorporate time specificity more explicitly in crime pattern theory, the term awareness space needs an even more dynamic conceptualization than the extended version as proposed by Bernasco (2010). He argued that "it takes time to become familiar with new places and routes as well as to forget former ones" (p. 393). This acknowledges the effects of time passing on spatial knowledge, but we suggest that not only such linear but also cyclic time patterns should be incorporated. Although people can to some extent infer time-invariant information regarding the places visited, some information will only be applicable to the specific time of day and day of week. Therefore, we suggest that people actually have a *time-specific awareness space* that relates their spatial knowledge to the time of day and day of week they visit the areas. Offenders would thus acquire time-specific knowledge about the potential costs and benefits associated with a specific crime location. Anecdotal evidence from a qualitative study on residential burglars illustrates the point:

> I always go back [to the same places] because, once you been there, you know just about when you been there before, and when you can go back. And every time I hit a house, it's always the same day [of the week] I done been before cause I know there ain't nobody there. (Offender #51; Wright and Decker 1994:69)

Hence, in the process of learning where to commit crime, we argue that the timing of previous offenses is also important. If an offender targeted a particular area at a specific part of the week or time of the day, the knowledge acquired about that area best applies to exactly that time period. For that reason, we expect that repeat offenders target areas they know to be attractive mainly at those days or times their knowledge applies. Moreover, we expect this learning effect to be the highest when *both* days and times are most similar. Following that offenders are more likely to commit a crime in an area where they have already offended before than in otherwise comparable areas where they have not offended before (see Lammers et al. 2015), our hypotheses read as follows:

Hypothesis 1a: Offenders are more likely to commit crime in areas they previously targeted at similar parts of the week than in areas where they had already offended before at different parts of the week.

Hypothesis 1b: Offenders are more likely to commit crime in areas they previously targeted at similar times of the day than in areas where they had already offended before at different times of the day.

Hypothesis 1c: Offenders are more likely to commit crime in areas they previously targeted when both days and times are similar than in areas where they had already offended before when days and times are different.

These first hypotheses are ignorant about the type of crime. Although crime pattern theory provides a generic explanation for where offenders commit crime, opportunity structures for different types of crime clearly vary. Consider the example of an offender who committed a burglary in a certain area. By doing so, the offender acquired knowledge about characteristics of the area that might be relevant for future burglaries such as levels of home occupancy in the area (Coupe and Blake 2006) and whether neighbors that could oversee the property were at home at the time of the offense (Rengert and Wasilchick 2000; Wright and Decker 1994). This knowledge is obviously time-specific and might be valuable information when the offender decides to commit another burglary, but it is probably less useful when the offender decides to commit another type of crime because home occupancy might not be a relevant factor that makes an area attractive for the other type of crime. Different types of crime simply require different knowledge about the opportunity structures (Lammers et al. 2015). Hence, we argue that offenders acquire *crime-specific time-specific knowledge* about the attractiveness of potential targets in an area. This leads to our second hypothesis that conditions Hypothesis 1c with respect to the type of crime:

Hypothesis 2: Offenders are more likely to commit crime in areas where they previously committed the same type of crime at similar days and times than in areas where they committed a different type of crime at similar days and times.

Data and Method

To study the impact of the timing of offenses on repeat offenders' crime location choices, an approach is needed that enables to explain why an offender commits crime at certain locations and which factors influence these choices. First introduced in the geography of crime by Bernasco and Nieuwbeerta (2005), discrete spatial choice models are well-suited to analyze such offender decision-making. These models allow the researcher to simultaneously assess the impact of offender characteristics (e.g., residential and offending histories) and characteristics of crime location alternatives (e.g., attractiveness of target areas) on the spatial criminal decision-making process. These models overcome important shortcomings of earlier approaches to the study of crime location choice that focused exclusively on either the offender (Gabor and Gottheil 1984; Hesseling 1992) or potential targets (Hakim, Rengert, and Shachmurove 2001; Sampson and Groves 1989; Velez 2001).

Discrete choice models distinguish four elements of a choice situation: the decision-maker, alternatives, attributes of the alternatives, and a decision rule (Ben-Akiva and Bierlaire 1999). In our case, the decision-maker is the offender who chooses a crime target area from a set of alternative target location areas that are mutually exclusive and collectively exhaustive. According to the decision rule, the offender chooses the alternative that maximizes the expected utility based on the attributes of the alternatives (Bernasco and Ruiter 2014; Ruiter 2017). Hence, offenders commit crime in those areas where they expect the rewards of crime to be highest, the risks lowest, and the least effort needed. In the present study, the alternatives represent the 142 different four-digit postal code areas of the study region, the greater The Hague area in the Netherlands. The area comprises of nine municipalities around—and including—the city of The Hague, the third largest city in the Netherlands. These postal code areas have an average population of approximately 7,000 residents and an average area size of about 2.96 km^2 (Lammers et al. 2015). In previous studies, it was argued that four-digit postal code areas are well-suited for crime location choice research, as these administrative areas were constructed in such a way to have minimal travel restrictions for postal delivery services that usually travel on foot or bicycle (Bernasco 2010:398). Hence, most people who live in or regularly visit an area should be familiar with that area. Besides, most previous crime location choice studies analyzed areas of a similar size (e.g., Bernasco and Nieuwbeerta 2005; Clare, Fernandez, and Morgan 2009; Townsley et al. 2015).

Data Sources

Information on offenders and their offenses was obtained from the Dutch Suspect Identification System (in Dutch "Herkenningsdienstsysteem [HKS]") used by The Hague Police Service. In HKS, Dutch police systematically recorded reports about suspects of serious types of crimes. It contains information on offender characteristics such as gender and age, as well as type, date, time, and location of their offenses. Although suspects who were charged with a crime were not necessarily convicted, approximately 90 percent of all suspects were found guilty at a later stage (Besjes and van Gaalen 2008; Blom et al. 2005). As the repeat offenders of our study population were charged with more than one offense, the percentage of conviction might be even higher for this group. The second source is a nationwide citizen information system, called BRP (in Dutch: "Basis Registratie Personen"). BRP is continuously updated with information on all residents of the Netherlands such as residential addresses and histories. Hence, these data provide valuable measures for offenders' current and past residential locations. In order to control for several important target area characteristics, the main data set was further supplemented with contextual data from two sources that contained year-specific information. First, for all Dutch postal code areas, Statistics Netherlands provides demographic and socioeconomic census-like statistics on a regular basis. Second, the LISA database (in Dutch: "Landelijk Informatiesysteem Arbeidsplaatsen") was used to obtain data on a variety of businesses and facilities in the Netherlands including bars, restaurants, supermarkets, retail stores, schools, and several leisure facilities (see Steenbeek et al. 2012).

Sampling Procedure

As this research extends the study of Lammers et al. (2015), it uses the same sample. From all suspects in the registration data of The Hague Police Service with at least one offense in 2009, a random sample of 10,000 suspects was drawn, and their registered offenses in the period 2006 to 2009 were obtained. In addition, their offense histories with a maximum of three years prior to these 2006 to 2009 offenses were included, thus ranging from 2003 to 2009. The following selections were made to obtain the final sample, consisting of repeat offenders who committed at least two crimes within a period of three years in the study area and who also lived in the area at the time of the offense. First, 4,244 single offenders were excluded because they had no crime history and consequently do not belong to our target population of repeat offenders. Second, 1,993 individuals did not have a known residential address within the study area or committed one of their offenses in a region outside the study area or study period. Third, 92 individuals were not involved in a felony and 5 individuals were younger than 12 years of age in 2009, and Dutch criminal law does not allow criminal prosecution under the age of 12. This results in a sample of 3,666 offenders who altogether committed 12,639 repeat offenses in one of the 142 potential target areas between 2006 and 2009 and who at least had committed one prior offense in the three years before.

Dependent Variable

The dependent variable represents the choice outcome, that is, the target area the offender has selected from the set of alternative areas. As all offense locations were geocoded and allocated to one of the 142 postal codes in the study area, the dependent variable describes the choice for a particular postal code from all 142 potential alternatives in the greater The Hague area. Several offenders had multiple repeat offenses during the study period (2006 to 2009), on average 3.45 offenses per offender. We used all these repeat offenses to test our hypotheses.

Independent Variables

In order to operationalize the main independent variables, all recorded offenses that offenders committed up to three years prior to each 2006 to 2009 offense were also geocoded and allocated to one of the 142 postal code areas. For each offense and the associated 142 alternative postal code areas, it is indicated whether the offender had committed a prior offense in that particular postal code in the previous three years. In the next paragraphs, the time variables that are constructed from these offense histories are described in more detail. If an offender committed several previous offenses in the three years prior to the 2006 to 2009 offense, all offenses were taken into account for the independent variable construction. In cases where the offender committed an offense on the exact same date as the previous offense (about 6 percent of the sample), one of the two offenses was randomly retained. Because there is no a priori best way to operationalize time similarity within the week and within the day, we used different temporal classifications to test which was most influential: (1) week-weekend differences, (2) differences by specific day of the week, (3) part of day differences (e.g., morning vs. afternoon), and (4) differences by specific hour of day.

Timing of crime within the week. In order to test Hypothesis 1a, several variables were constructed based on the recorded offense dates. As routine activities vary between the weekend and workweek but also within, five different variables were created that represent all possible combinations: offenses committed during the same part of the week (i.e., week-week or weekend-weekend) versus a different part of the week (i.e., week-weekend or weekend-week) and at the same versus a different day of the week. First, the dichotomous variable *previous crime location on same weekday* (1 = *yes*; 0 = *no*) was constructed to indicate whether the offender had committed a prior offense in a particular postal code during the exact same workweek day (Monday, Tuesday, Wednesday, Thursday, or Friday) as the subsequent offense. For example, a particular area received a score of 1 if the previous offense had been committed in that area on a Tuesday and a subsequent offense was also committed on a Tuesday. *Previous crime location on different weekday* (1 = *yes*; 0 = *no*) was created similarly, the only difference being that the subsequent crime was committed on a different day of the workweek. In a similar manner, the dichotomous variables *previous crime location on same weekend day* (1 = *yes*; 0 = *no*) and *previous crime location on different weekend day* (1 = *yes*; 0 = *no*) were constructed. With regard to the latter, for example, a particular target area was assigned a score of 1 if the previous offense was committed in the area on a Saturday and the subsequent offense on a Sunday. Lastly, the dichotomous variable *previous crime location on different week part* (1 = *yes*; 0 = *no*) indicated whether the offender had committed a previous offense in a particular area during a different part of the week (i.e., week-weekend or weekend-week)—and therefore automatically on a different day of the week—compared to when the subsequent offense was committed.

Timing of crime within the day. For testing Hypothesis 1b, different variables were constructed based on the recorded offense times. First, the dichotomous variables *previous crime location with a ... hour difference* (1 = *yes*; 0 = *no*) were created, ranging from zero hours, one to two hours, three to five hours, and greater than six hours difference. These variables indicated whether the offender had committed a previous offense in a particular postal code at the same or a different time of day, and if different, how much so. Subsequently, four six-hour intervals were defined: morning (6 a.m. to noon), afternoon (noon to 6 p.m.), evening (6 p.m. to midnight), and night (midnight to 6 a.m.). The four hour-difference variables were subdivided for previous and subsequent offenses that were committed on the same daypart (i.e., both in the afternoon) and for offenses that were committed on a different part of the day (see Table 1 for the complete list of variables). For example, if the previous offense was committed in a particular postal code at 8 p.m. and the subsequent offense at 5 a.m., a score of 1 was assigned to the variable *previous crime location on different daypart with a greater than six-hour difference*. If both offenses were committed at exactly the same time of day, a score of 1 was assigned to the variable *previous crime location on same daypart with a zero-hour difference*. Because all dayparts consist of six-hour time periods, the variables *previous crime location on same daypart with a greater than six-hour difference* and *previous crime location on different daypart with a zero-hour difference* can only score a 0 and are therefore left out of the analysis.

Timing of crime within the week and day combined. After separately testing the effects of the specific week parts, days of the week, dayparts, and hours of the day, a combined model was estimated to examine whether offenders are more likely to offend in a previously targeted area when both the timing within the week and within the day are more similar to that of the previous offense. For example, would an offender who already committed a crime in a certain area at 12 p.m. on Saturday be more likely to strike there again on another Saturday at 12 p.m. than on a totally different part of the week and day? Based on the findings from the models in which separate time-specific effects were estimated (see models 1 and 2 in Table 2), the most distinctive temporal categories of timing within the week and timing within the day were used to construct the temporal classification that combined timing within the week and day: *previous crime location on . . . with a . . . hour difference* (see model 3 in Table 3).

It is important to note that the date and time of the offenses in the Dutch police records were listed as start and end dates and times. For about one-fifth of the offenses, the start and end dates and/or times were different, ranging from very small differences within the hour to major differences within the week. This is most likely due to the fact that for some types of crime (e.g., residential burglaries), the victim is generally not present at the time of the offense and can therefore not reliably report on the exact timing of the offense (Ratcliffe 2002). Also, the nature of certain offenses naturally leads to larger time periods than one single point in time. The end dates and times were used to construct the time variables used in the analysis. These recordings are expected to yield the most accurate information because a crime can only be determined after it is committed. As a robustness check, the analyses were repeated with a sample that only consists of the 9,235 offenses committed by 3,187 offenders, for which exact dates (i.e., no differences between the starting and ending date) and times (i.e., no differences between the starting and ending hour) were recorded.

Type of crime. For the test of Hypothesis 2, the dichotomous variables *previous crime of the same type* (1 = *yes*; 0 = *no*) and *previous crime of a different type* (1 = *yes*; 0 = *no*) were created to indicate whether the previous offense was of the same or different crime type as the subsequent offense. The crime types were based on the classification scheme as used by Statistics Netherlands (2014): violence, property, vandalism, traffic, environmental, drugs, weapons, and other types of crime. These variables were interacted with the time variables as used in the combined model (see model 4 in Table 3).

Control Variables

Several control variables were included in the analysis as they were expected to influence crime location choice and are possibly also related to our study variables. Table 1 shows summary statistics for the offense-alternative and potential target area characteristics. First, we control for offender's *current or former residence* (1 = *yes*; 0 = *no*) and *distance from current residential area* to the target area alternatives (ranging from 0.2 to 27.4 km). Offenders are assumed to have more knowledge on areas that are closer to their homes than on areas further away (Bernasco 2010; Bernasco and Kooistra 2010). Bernasco (2010) showed that offenders were more likely to commit crime in an area where they were living at the time of or before the offense than in otherwise comparable areas. Therefore, all home addresses inside the study area were geocoded and allocated to 1 of the 142 postal code areas. Euclidian distances between the centroids of the offender's current residential postal code area and each alternative postal code area were used. Distances of zero (i.e., the offender's own residential postal code area) were replaced by the average distance between two random points in that postal code area, approximated by .49 times the square root of the size of the area in square kilometers (see Lammers et al. 2015).

Furthermore, previous studies have shown that several target area characteristics, such as indicators of guardianship or crime attractors and generators, affect crime rates (e.g., Bernasco and Block 2011; Bernasco and Nieuwbeerta 2005; Cohen and Felson 1979). The following target area characteristics from Statistics Netherlands were taken into account: *proportion of residents with a non-Western background* (ranging from 0 to 1), *proportion of single-person households* (ranging from 0 to 1), and *population density*, calculated by

Table 1. Summary Statistics of Offense-alternative Characteristics for 12,639 Repeat Offenses Committed by 3,666 Offenders ($N = 1,787,105$) and Characteristics of the Potential Target Areas[a] ($N = 142$).

Variable	Mean/ Proportion	Standard Deviation	Min.	Max.	*N*
Timing of crime within the week					
Previous crime location on					
Same weekend day	0.002	—	0	1	1,787,105
Different weekend day	0.001	—	0	1	1,787,105
Same weekday	0.003	—	0	1	1,787,105
Different weekday	0.009	—	0	1	1,787,105
Different week part	0.010	—	0	1	1,787,105
Timing of crime within the day					
Previous crime location on					
Same daypart[b] with					
0 hour difference	0.003	—	0	1	1,787,105
1-2 hour difference	0.005	—	0	1	1,787,105
3-4 hour difference	0.002	—	0	1	1,787,105
Different daypart with					
1-2 hour difference	0.002	—	0	1	1,787,105
3-4 hour difference	0.005	—	0	1	1,787,105
>6 hour difference	0.009	—	0	1	1,787,105
Control variables					
Current or former residence	0.012	—	0	1	1,787,105
Distance from current residential area	7.942	4.667	.172	27.338	1,787,105
Proportion of non-Western residents	0.189	0.183	0	0.875	142
Proportion of single-person households	0.391	0.147	0	0.693	142
Population density (per 1,000)	6.338	6.395	.023	42.844	142
Number of employees (per 1,000)	3.440	3.554	.002	20.520	142
Retail business (per 10)	5.645	5.806	0	36.400	142
Hotels, restaurants, and bars (per 10)	2.258	3.049	0	21.100	142
Schools (per 10)	1.254	0.722	0	3.800	142
Health-care facility (per 10)	1.459	1.254	0	7.400	142
Cultural facility (per 10)	1.618	1.117	0	22.500	142
Sports and leisure facility	4.107	3.230	0	18.000	142

[a]Target area characteristics were calculated as the average for the years 2006 to 2009. Information from one postal code area (2643, "Pijnacker") was missing for the years 2006 to 2008 ($N = 7,633$) because it only became a residential area by the year 2009. The averages for that postal code area were thus exclusively based on the year 2009. Therefore, the final data set contains 1,787,105 offense-alternative cases; for the year 2009, we have 142 alternative postal code areas and for all other years 141. [b]Four equally divided dayparts ranging from morning (6 a.m.-noon), afternoon (noon-6 p.m.), evening (6 p.m.-midnight), and night (midnight-6 a.m.). Because the four different dayparts consist of six-hour time periods, the variables *previous crime location on the same daypart with a greater than six-hour difference* and *previous crime location on different daypart with a zero-hour difference* do not yield any scores and are therefore left out of the table.

dividing the number of residents in each postal code by its surface in square kilometers. Using information from the LISA database, we also controlled for the *number of employees* and several variables that count the presence of a variety of facilities in each postal code (see Table 1). These facilities are expected to attract flows of people that, depending on the specific type of crime, could function as potential targets as well as possible guardians. All contextual variables were constructed using year-specific information that relates to the year of the offense under study (2006 to 2009).

Method

Conditional logit models[1] were used to test our hypotheses. For this purpose, a large data matrix of 1,787,105 rows was constructed containing 142 rows (i.e., target alternatives) for each of the 12,639 offenses to be explained.[2] The results of the conditional logit models are presented using odds ratios (*OR*s) and their respective standard errors (*SE*s). The *OR*s represent the multiplicative effect of a unit increase of the study variables on the odds of selecting 1 of the 142 potential target areas. The independent study variables score 0 when an offender never targeted a certain area before. Therefore, the effects of all study variables are expected to be positive with *OR*s greater than 1. More important for testing our hypotheses, differences *between OR*s were tested using Wald's Chi-Square difference tests. These tests reveal whether the *OR*s differ statistically significantly between the study variables of interest: committing a crime in an area that the offender already targeted before at similar versus different parts of the week (model 1), similar versus different times of the day (model 2), similar versus different parts of the week and day combined (model 3), and similar versus different types of crime (model 4). To account for the fact that multiple offenses are nested within offenders, cluster-corrected *SE*s were estimated.

Results

Timing of Crime within the Week (Hypothesis 1a)

After estimating a baseline model with the control variables only (model 0, Table 2), the first hypothesis was tested. Model 1 in Table 2 shows that offenders are more likely to commit crime in previously targeted areas on the *same weekend day* than in any other potential target area ($OR = 6.38$, $p < .001$). When committing an offense on a *different weekend day*, offenders are still more likely to return to a previously targeted area, although the OR ($OR = 2.93$, $p < .001$) is statistically significantly smaller, $\chi^2(1) =$

41.18, $p < .001$. When looking at the timing of crime within the Monday to Friday workweek, the odds to offend in a particular target area were 4.26 times larger when the offender already targeted that area before on the *same weekday*, compared to an *OR* of 3.82 when the previous offense was committed on a *different weekday*. The difference between these effects was not statistically significant, $\chi^2(1) = 1.52$, $p = .218$. Lastly, we observe that the odds to offend in a particular target area were only 3.02 times larger when the offender already targeted that area before on a *different part of the week* (i.e., week-weekend or weekend-week) than when the offender had not committed a crime in that area before. This *OR* was statistically significantly lower than the previously described *OR*s regarding offenses committed in the same part of the week, both during the workweek and or during the weekend, $\chi^2(4) = 73.72$, $p < .001$. Taken together, these results support Hypothesis 1a. It seems particularly important to not only examine differences between the weekend and the rest of the week but also take specific days of the week into account, especially within the weekend.

Timing of Crime within the Day (Hypothesis 1b)

In model 2 of Table 2, we observe that the effects of all hour-difference variables were positive and statistically significant. The size of the *OR*s for offenses that were committed on the *same daypart* decreased from 9.38 when committed in an area that the offender previously targeted at the exact *same hour of the day* to 3.67 when committed in areas that the offender previously targeted with a *three- to five-hour difference*. A joint test showed that the effects of the consecutive pairs of all three hour-difference variables (i.e., zero-hour difference vs. one- to two-hour difference and one- to two-hour difference vs. three- to five-hour difference) differed statistically significantly, $\chi^2(2) = 166.87$, $p < .001$. When the previous offense was committed on a *different part of the day*, a similar decreasing trend in effect sizes is observed but with smaller *OR*s, $\chi^2(2) = 38.37$, $p < .001$. In line with Hypothesis 1b, the results indicate that offenders are more likely to target areas where they have already offended before at similar times of the day than areas where they have offended before at different times of the day. The findings also show that important hourly differences would be overlooked when only the four different six-hour periods of the day (i.e., morning, afternoon, evening, and night) are distinguished. Therefore, the hour-difference intervals are used for our integrated model of the timing of crime within the week and day combined.

Table 2. Conditional Logistic Regression Models Testing the Effects of Timing of Crime within the Week and Timing of Crime within the Day on Repeat Offenders' Crime Location Choices.

	Model 0		Model 1		Model 2	
	Control Variables Only		Timing of Crime within the Week (H1a)		Timing of Crime within the Day (H1b)	
Variable	*OR*	*SE*	*OR*	*SE*	*OR*	*SE*
Timing of crime within the week						
Previous crime location on						
Same weekend day			6.384***	(.551)		
Different weekend day			2.930***	(.328)		
Same weekday			4.256***	(.253)		
Different weekday			3.815***	(.171)		
Different week part			3.023***	(.133)		
Timing of crime within the day						
Previous crime location on						
Same daypart[a] with						
0 hour difference					9.384***	(.620)
1-2 hour difference					4.799***	(.250)
3-5 hour difference					3.674***	(.253)
Different daypart with						
1-2 hour difference					5.158***	(.447)
3-5 hour difference					4.361***	(.248)
>6 hour difference					3.378***	(.141)
Control variables						
Current or former residence	6.177***	(.282)	3.465***	(.137)	3.377***	(.134)
Distance from current residential area	0.694***	(.007)	0.731***	(.005)	0.733***	(.005)
Proportion non-Western residents	2.392***	(.197)	2.322***	(.163)	2.292***	(.160)
Proportion single-person households	1.525**	(.235)	1.897***	(.245)	1.894***	(.244)
Population density (per 1,000)	0.992**	(.003)	0.993**	(.002)	0.993**	(.002)
Number of employees (per 1,000)	1.031***	(.004)	1.027***	(.003)	1.026***	(.003)
Retail business (per 10)	1.050***	(.006)	1.036***	(.005)	1.035***	(.004)
Hotels, restaurants, and bars (per 10)	1.011*	(.011)	1.016*	(.008)	1.016*	(.008)

(continued)

Table 2. (continued)

	Model 0		Model 1		Model 2	
	Control Variables Only		Timing of Crime within the Week (H1a)		Timing of Crime within the Day (H1b)	
Variable	*OR*	*SE*	*OR*	*SE*	*OR*	*SE*
Schools (per 10)	1.073**	(.028)	1.043*	(.024)	1.054*	(.024)
Health-care facility (per 10)	0.949***	(.014)	0.974*	(.013)	0.974*	(.013)
Cultural facility (per 10)	1.011**	(.004)	1.008*	(.003)	1.007*	(.003)
Sports and leisure facility	1.027***	(.005)	1.025***	(.004)	1.025***	(.004)
AIC	92,043		85,973		85,308	
Pseudo R^2	.265		.313		.318	

Note: N = 1,787,105 offense alternatives for 12,639 repeat offenses, committed by 3,666 offenders. *OR* = odds ratio coefficient; *SE* = standard error corrected for clustering within offenders; AIC = Akaike information criterion.

[a]Four equally divided dayparts ranging from morning (6 a.m.-noon), afternoon (noon-6 p.m.), evening (6 p.m.-midnight), and night (midnight-6 a.m.). Because the four different dayparts consist of six-hour time periods, the variables *previous crime location on the same daypart with a greater than six-hour difference* and *previous crime location on different daypart with a zero-hour difference* do not yield any scores and are therefore left out of the analysis.

*p < .05. **p < .01. ***p < .001 (two-tailed).

Combined Model: Timing of Crime within the Week and Day (Hypothesis 1c)

Model 3 (Table 3) presents a combined model for the hypothesized time effects within the week and day simultaneously. Similar as the results in model 2, a pattern of decreasing effect sizes is observed within each "block" of the four hour-difference variables (i.e., zero-hour difference vs. one- to two-hour difference, one- to two-hour difference vs. three- to five-hour difference, and three- to five-hour difference vs. greater than six-hour difference) for each of the five time categories within the week. For example, the odds to offend in a particular target area were 25.77 times larger when the offender already targeted that area before on the *same weekend day with a zero-hour difference* than when the offender had not committed a crime in that area before. The *OR*s decreased to 3.22 when both crimes were committed on the *same weekend day with a greater than six-hour difference*.

Table 3. Conditional Logistic Regression Models Testing the Effects of Timing of Crime within the Week and Day on Repeat Offenders' Crime Location Choices for Same versus Different Types of Crime.

	Model 3		Model 4			
	Timing within the Week and Day (H1c)		Timing within the Week and Day by Crime Type (H2)			
			Same Crime Type		Different Crime Type	
Variable	*OR*	*SE*	*OR*	*SE*	*OR*	*SE*
Previous crime location on						
Same weekend day with						
0 hour difference	25.766***	(5.367)	45.773***	(13.293)	8.476***	(2.609)
1-2 hour difference	7.826***	(1.043)	10.785***	(2.027)	3.624***	(0.719)
3-4 hour difference	4.392***	(0.591)	4.963***	(1.067)	2.691***	(0.580)
>6 hour difference	3.220***	(0.445)	4.313***	(0.849)	1.968***	(0.349)
Different weekend day with						
0 hour difference	5.014***	(1.391)	4.927***	(2.077)	4.764***	(1.724)
1-2 hour difference	3.466***	(0.558)	3.856***	(0.970)	2.545***	(0.574)
3-4 hour difference	2.888***	(0.448)	2.928***	(0.543)	1.998*	(0.555)
>6 hour difference	2.273***	(0.317)	2.055**	(0.349)	1.998***	(0.331)
Same weekday with						
0 hour difference	18.016***	(3.426)	26.144***	(6.419)	5.656***	(1.512)
1-2 hour difference	4.638***	(0.497)	6.113***	(0.842)	2.593***	(0.461)
3-4 hour difference	2.819***	(0.330)	3.881***	(0.594)	1.532**	(0.251)
>6 hour difference	2.304***	(0.253)	2.423***	(0.380)	1.518**	(0.232)

(continued)

Table 3. (continued)

	Model 3		Model 4			
	Timing within the Week and Day (H1c)		Timing within the Week and Day by Crime Type (H2)			
			Same Crime Type		Different Crime Type	
Variable	*OR*	*SE*	*OR*	*SE*	*OR*	*SE*
Different weekday with						
0 hour difference	5.965***	(0.615)	6.988***	(0.963)	2.442***	(0.462)
1-2 hour difference	4.458***	(0.299)	4.323***	(0.399)	2.570***	(0.249)
3-4 hour difference	3.865***	(0.254)	3.572***	(0.336)	2.574***	(0.236)
>6 hour difference	3.028***	(0.191)	3.043***	(0.265)	1.949***	(0.175)
Different week part with						
0 hour difference	4.315***	(0.412)	4.507***	(0.626)	2.625***	(0.418)
1-2 hour difference	3.375***	(0.237)	3.200***	(0.341)	2.563***	(0.231)
3-4 hour difference	2.999***	(0.199)	2.951***	(0.290)	2.106***	(0.191)
>6 hour difference	2.621***	(0.148)	2.555***	(0.241)	2.002***	(0.143)
Control variables						
Current or former residence	3.529***	(0.135)	3.742***	(0.142)	3.742***	(0.142)
Distance from current residential area	0.731***	(0.005)	0.728***	(0.005)	0.728***	(0.005)
Proportion non-Western residents	2.344***	(0.164)	2.381***	(0.169)	2.381***	(0.169)
Proportion single-person households	1.898***	(0.243)	1.864***	(0.239)	1.864***	(0.239)
Population density (per 1,000)	0.993**	(0.002)	0.993**	(0.002)	0.993**	(0.002)
Number of employees (per 1,000)	1.026***	(0.003)	1.027***	(0.003)	1.027***	(0.003)

(continued)

Table 3. (continued)

	Model 3		Model 4			
	Timing within the Week and Day (H1c)		Timing within the Week and Day by Crime Type (H2)			
			Same Crime Type		Different Crime Type	
Variable	*OR*	*SE*	*OR*	*SE*	*OR*	*SE*
Retail business (per 10)	1.034***	(0.004)	1.034***	(0.004)	1.034***	(0.004)
Hotels, restaurants, and bars (per 10)	1.019*	(0.008)	1.019*	(0.008)	1.019*	(0.008)
Schools (per 10)	1.050*	(0.024)	1.053*	(0.024)	1.053*	(0.024)
Health-care facility (per 10)	0.974*	(0.013)	0.972*	(0.012)	0.972*	(0.012)
Cultural facility (per 10)	1.008*	(0.003)	1.009**	(0.003)	1.009**	(0.003)
Sports and leisure facility	1.025***	(0.004)	1.026***	(0.004)	1.026***	(0.004)
AIC	85,394		85,477		85,477	
Pseudo R^2	.319		.318		.318	

Note: N = 1,787,105 offense alternatives for 12,639 repeat offenses, committed by 3,666 offenders. *OR* = odds ratio coefficient; *SE* = standard error corrected for clustering within offenders; AIC = Akaike information criterion.
*p < .05. **p < .01. ***p < .001 (two-tailed).

The *OR*s of the consecutive pairs of hour-difference variables differed statistically significantly, $\chi^2(3) = 87.46$, $p < .001$.

A similar but somewhat smaller decreasing pattern was found when both offenses were committed during the *same day of the week*, $\chi^2(3) = 92.61$, $p < .001$. We still observe a decay in effect sizes for crimes committed on a different weekend day, $\chi^2(3) = 9.30$, $p = .026$; different day of the work-week, $\chi^2(3) = 39.20$, $p < .001$; and different part of the week, $\chi^2(3) = 26.41$, $p < .001$. However, the *OR*s are expectedly smaller compared to those within the same part of the weekend or week. The joint test showed that the *OR*s of the consecutive pairs of the hour-difference variables differed statistically significantly between all the five week categories, $\chi^2(15) = 329.13$, $p < .001$. An additional joint test, $\chi^2(4) = 2018.42$, $p < .001$, showed that the *OR*s for the most similar time categories (i.e., on the exact same weekend or weekday with a zero-hour difference between the offenses) differed statistically significantly from the most different time categories (i.e., on a different part of the week with a greater than six-hour difference between the offenses). We can thus conclude that Hypothesis 1c is also supported.

Combined Model for Same versus Different Types of Crime (Hypothesis 2)

Model 4 (Table 3) presents our final model with simultaneous effect size estimates for offense pairs of the same versus a different type of crime. As in model 3, all effects of the study variables are positive and statistically significant. Again, we observe the highest *OR*s and the largest effect size differences between the four hour-difference categories when the previous offense was committed on the exact same day of the weekend, followed by previous offenses committed on the same weekday. More importantly, we observe that the effects are much stronger when offense pairs are of the *same type of crime* than when they are of a *different crime type*, $\chi^2(20) = 135.63$, $p < .001$. In line with Hypothesis 2, offenders are more likely to commit crime in areas where they previously committed the same type of crime at similar days and times than in areas where they committed a different type of crime at similar days and times.

Model Fit and Robustness Check

The models in which the time-specific effects for previously targeted areas were taken into account (models 1–4, Tables 2 and 3) show a pseudo R^2 of .32. This is a substantial increase compared to the pseudo R^2 of .26 of the baseline model (model 0, Table 2) in which previous crime locations and their timing were not included. Previous offense locations thus provide an important part of the explanation of where repeat offenders commit crime. According to McFadden (1973), pseudo R^2 values between .2 and .4 represent an excellent fit for discrete choice models, especially when analyzing large choice sets. To check the robustness of our findings, we reestimated all models with an adjusted data set (N = 1,305,994) that only included offenses with precisely recorded dates and times (see Data and Method section). The results (not shown here) confirm the overall conclusions with regard to our hypotheses.

Discussion

This article investigated to what extent the likelihood that offenders return to previously targeted areas is conditional on the timing of previous and subsequent offenses within the week and within the day. Extending crime pattern theory, we argued that offenders acquire time-specific rather than general knowledge about criminal risks, rewards, and opportunities in their activity space. This was expected to influence the locations where offenders subsequently choose to offend. Analyzing the crime location choices of 3,666 repeat offenders using discrete spatial choice models, we confirmed that offenders are more likely to commit crime in previously targeted areas than in areas where they had not committed offenses before. In line with our hypotheses, we found that the likelihood to commit crime in previously targeted areas was much stronger when offenders committed the previous offense during similar parts of the week or similar times of the day than when they previously targeted the area at different parts of the week and different times of day. Particularly, repeat offenders most likely offend in areas they already targeted before on the exact same weekend day or weekday with only a zero- to two-hour difference between the offense times. This confirms Hypotheses 1a and b. Offenders do not just return to previously targeted areas, they are much more likely to do so when committing the offense at a similar day or time.

Another important finding of the present study is that our hypothesized time effects also hold when tested simultaneously (Hypothesis 1c). In fact, our results show that differences between days of the week and time of the day should be analyzed in conjunction. If we had only tested our hypotheses in separate models, we would have wrongly concluded that there is no need to differentiate between specific days of the workweek. Our integrated model, however, does show that offenders are more likely to return to previously targeted areas at the same day of the workweek, but mainly when the offenses were committed on the exact same hour of day. Hence, our findings indicate that for a better understanding of the spatiotemporal aspects of criminal decision-making, it is important to take both part of week and time of day into account.

Our results correspond with findings from previous studies outside the crime location choice framework that looked at the timing of offenses within the week (e.g., Andresen and Malleson 2015; Johnson et al. 2012) and day (e.g., Haberman and Ratcliffe 2015; Sagovsky and Johnson 2007). For example, Sagovsky and Johnson (2007) compared initial and subsequent burglary victimizations in Australia and found that more than 60 percent of the repeat events occurred within the same eight-hour period of the day. More generally, our findings provide support for crime pattern theory as Brantingham and Brantingham (1981) already stressed the importance of time next to space in their earlier work. However, the findings also suggest that the term awareness space needs an even more dynamic conceptualization than the extended version proposed by Bernasco (2010); not only linear but also cyclic time patterns should be incorporated. We therefore propose the term *time-specific awareness space* that relates people's spatial knowledge to the time of day and day of week they visit the areas.

These results are not only important for how we should think about the time specificity of offenders' awareness spaces and how this provides a better explanation of their crime location choices. They could also be used to improve predictive policing methods that strongly rely on the near-repeat phenomenon (e.g., Bowers, Johnson, and Pease 2004; Mohler et al. 2015; Rummens, Hardyns, and Pauwels 2017). Our findings show that the likelihood to return to previously targeted areas is actually increased at similar days of the week and similar times of the day, whereas most predictive policing applications do not take such cyclic time effects into account but merely rely on spatial and temporal decay functions. Although Johnson et al. (2007) already developed a predictive approach that takes cyclic time patterns in repeat victimizations into account, virtually all recent work on predictive policing seems to have overlooked such patterns (for an exception, see Rummens et al. 2017). In this study, we started from an offender's perspective and we found support for cyclic time patterns in crime location choice. This stresses the importance for future predictive policing methods to combine spatiotemporal decay functions and cyclic time effects within the week and day. Moreover, our findings imply that also time-specific situational preventive measures that make a targeted area less attractive on similar days and times of previous crimes could help preventing future crime in that area (e.g., improve lighting in an area that was targeted at night).

Although the present study offers important insights into offenders' spatiotemporal criminal decision-making, some caveats and opportunities for future research should be mentioned. First, this study relies on police data regarding arrested offenders. As only a proportion of all crimes are solved by the police, the results from this study might suffer from detection bias. The question remains whether we can generalize our findings to non-arrested offenders because there might be differences in the probability of arrest between first offenders and offenders who committed multiple offenses in the same area. In fact, our findings could to some extent reflect police detection strategies that focus on repeat offenders. However, recent research suggests that detection bias is not as large as has often been assumed in previous literature (Johnson et al. 2009; Lammers 2014; Summers, Johnson, and Rengert 2010). These studies found little evidence that solved and unsolved offenses display large spatiotemporal differences.

Nevertheless, the fact that our offender population was arrested for offenses committed at a certain place and time might seem contradicting to our predictions based on rational choice and crime pattern theory. From a purely rational choice perspective, one would expect that offenders adjust their cost-benefit analysis after they get caught in ways that previous offense locations and times will be perceived as less attractive. However, following crime pattern theory, familiarity with a certain area is one of the most important determinants for target selection. Although rational offenders would prefer to offend in areas where they were never caught before, they might still rather go to places *within* their awareness space where they were caught than to go outside this familiar environment where they have never been before (and hence never been caught) and thus lack the required spatial knowledge of criminal opportunities. It requires detailed offender data on both solved and unsolved cases to examine which mechanism most strongly drives crime location choice. Another possible explanation for why offenders return to previously targeted areas even if they were arrested could be that those that got caught reduce their sanction certainty estimate based on a belief that they would have had to be exceedingly unlucky to get arrested. This is also known as the "gamblers fallacy" (Pogarsky and Piquero 2003).

Second, our hypotheses are built on the assumption that offenders actively learn about suitable targets at particular times and days and that they subsequently use this information in their future spatiotemporal criminal decision-making. However, we did not explicitly test such an underlying "state dependence" mechanism, and other explanations for our findings are also possible. For example, offenders might be constrained by their own daily routine activities, which forces them to engage in consistent and habitual behavior over time (Hägerstrand 1970; Ratcliffe 2006). The findings could also reflect how opportunities for crime vary across areas and times. Unfortunately, our data do not allow us to distinguish between these different types of explanations, and hence, we could not empirically assess the extent to which these other mechanisms might explain our findings. However, the offense-type-specific effects of this study provide a first step in trying to understand the underlying mechanism. The finding that offenders have a higher chance to strike in a previously targeted area at similar times of the day and week *especially* when the previous and subsequent offenses were of the same type of crime provides tentative support for the proposed rational choice explanation over the alternative routine activity explanation. Apparently, particular crime type–specific knowledge acquired during a previous offense might make the target area attractive for committing that same type of crime again on a similar day and at a similar time, while it might not influence whether an area is attractive for other types of crimes.

Third, we analyzed offenders' crime location choice behavior *given* the time they committed their offenses instead of treating the timing of the crime as a choice itself. There are several possible scenarios for how the timing and place of a crime are the result of offender decision-making: (1) Offenders indeed choose their crime locations given a certain time, as assumed in this study, (2) offenders choose the timing of their crimes given the location, (3) both the location and timing of a crime are chosen, and these decisions need not be independent, or (4) offenders choose whether to commit a crime given the time and location. More research into these scenarios could also shed light on the long-standing criminological debate about whether crime journeys start with the explicit intention to offend (planned behavior) or whether offenders commit crime more impulsively during ordinary activities based on the opportunities at hand (opportunistic behavior). However, the current data and methods do not allow us to distinguish the different scenarios empirically.

In order to shed more light on the planned-opportunistic distinction and the role of time of day and part of week within offender decision-making, future studies could measure which other activity nodes than the ones currently available for research are visited by offenders and when they are usually visited. Examples include the locations of offenders' schools, work, leisure activities, and home locations of their family and friends. A recent study made a first step showing that offenders are also more likely to target residential areas of close family members (Menting et al. 2016). Another way forward is through offender interviews in which offenders are asked more specifically about their routines as well as spatiotemporal preferences. Future research might also take more direct measures of time-varying target attractiveness into account, for example, by focusing on effects of opening and closing hours of facilities and businesses on crime location choices. As most businesses are not open 24/7, it seems unrealistic to assume that offenders would be attracted to potentially criminogenic facilities irrespective of time of day, although two recent studies found surprisingly stable effects of target attractiveness (Bernasco et al. 2017; Haberman and Ratcliffe 2015). When we would know the exact hours and days facilities are open, their influence on crime patterns could be more realistically assessed. To examine time-varying target attractiveness that relate more specifically to certain crime types such as bike theft, car theft, or robbery, future research might also consider carrying out systematic observations to determine variations in, for example, the number of bicycles, motor vehicles, or people in a given area.

To conclude, the main finding of our study emphasizes that the understudied role of time of day and part of week in crime location choice studies deserves more attention. Extending crime pattern theory by adding a cyclic time dimension to awareness spaces, the present study contributed to the geography of crime literature by stressing that offenders' knowledge about potential risks, rewards, and opportunities could no longer be conceptualized as completely time-invariant. For a better understanding of offenders' spatial criminal decision-making, both offenders' previous crime locations and their timing within the day and week need to be taken into account. Hence, there is not only a place but also a time for a crime.

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Notes

1. Although the more flexible mixed logit model was recently used (Frith, Johnson, and Fry 2017; Townsley et al. 2016), we use the conditional logit model as originally proposed by McFadden (1973) and most commonly used in crime location choice research (Ruiter 2017). Given the nature of the Bayesian estimation technique, the task to estimate a mixed logit model for a research problem the size of ours exceeds the limits of most contemporary computer workstations. We estimated it would have taken us several months to estimate a single model using Stata/MP version 11 running on our workstation with two Intel Xeon 4-core CPUs at 2.27 GHz with 32 GB RAM.
2. Information from one postal code area (2643, "Pijnacker") was missing for the years 2006-2008 ($N = 7{,}633$) because it only became a residential area by the year 2009. Therefore, the final data set contains 1,787,105 offense-alternative cases; for the year 2009, we have 142 alternative postal code areas and for all other years 141.

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