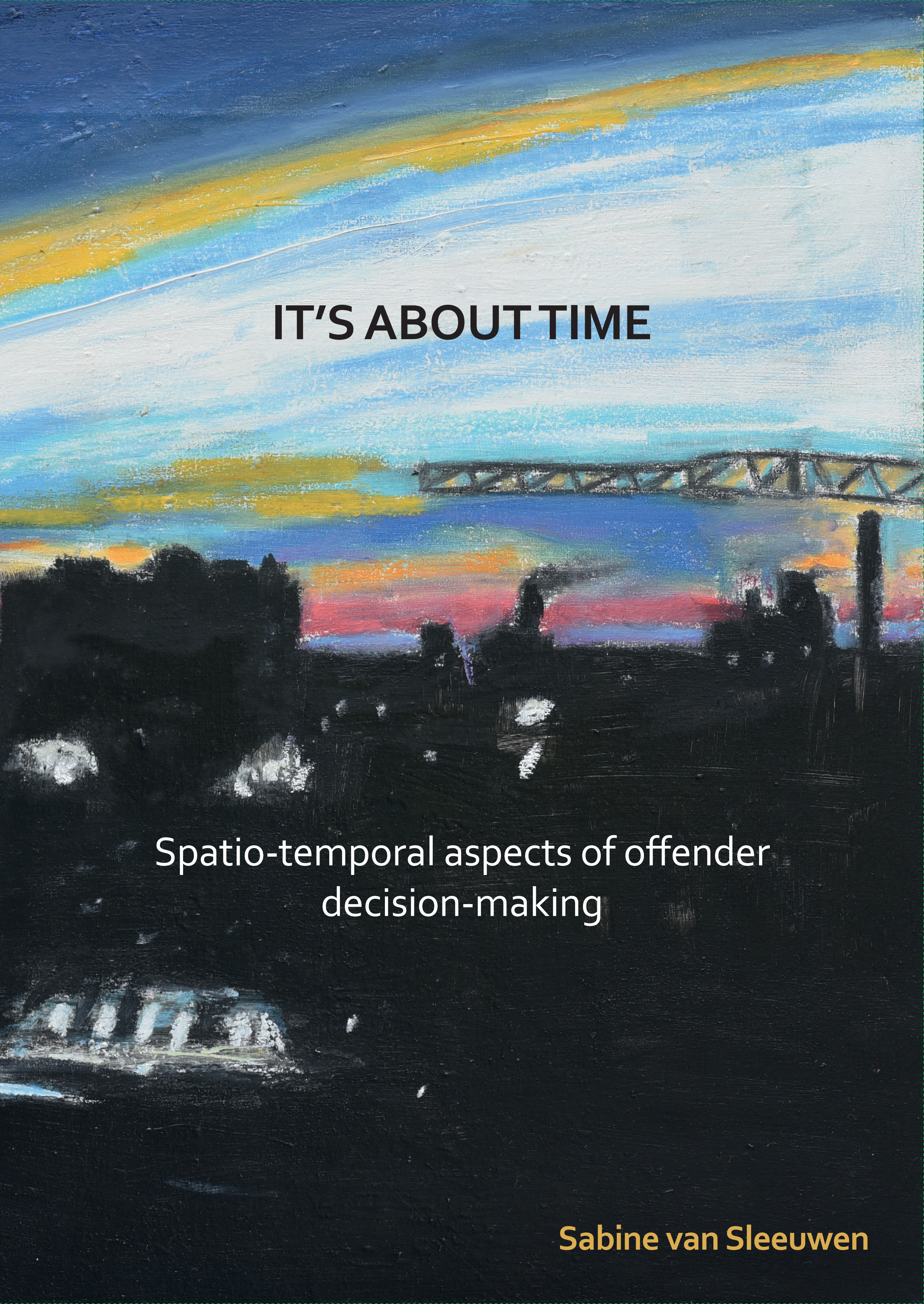

IT'S ABOUT TIME

Spatio-temporal aspects of offender decision-making

Sabine van Sleeuwen

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Sabine Elise Marie van Sleeuwen

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IT'S ABOUT TIME

Spatio-temporal aspects of offender decision-making

DE HOOGSTE TIJD

Ruimtelijk-temporele aspecten in het keuzegedrag van daders

(met een samenvatting in het Nederlands)

Proefschrift

ter verkrijging van de graad van doctor aan de
Universiteit Utrecht op gezag van de rector magnificus,
prof.dr. H.R.B.M. Kummeling, ingevolge het besluit van het
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door

Sabine Elise Marie van Sleeuwen

geboren op 4 september 1991
te 's-Hertogenbosch

Promotor: Prof. dr. S. Ruiter

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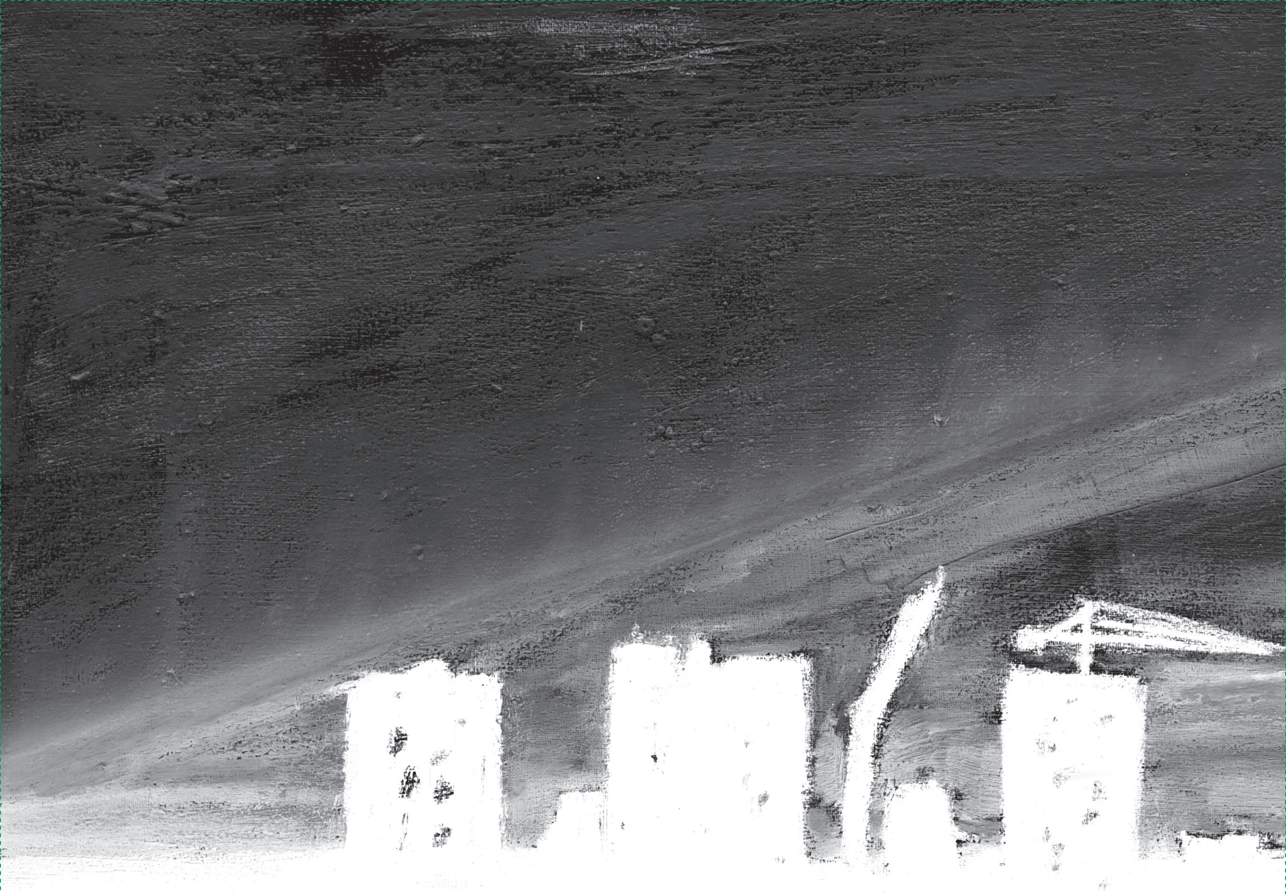

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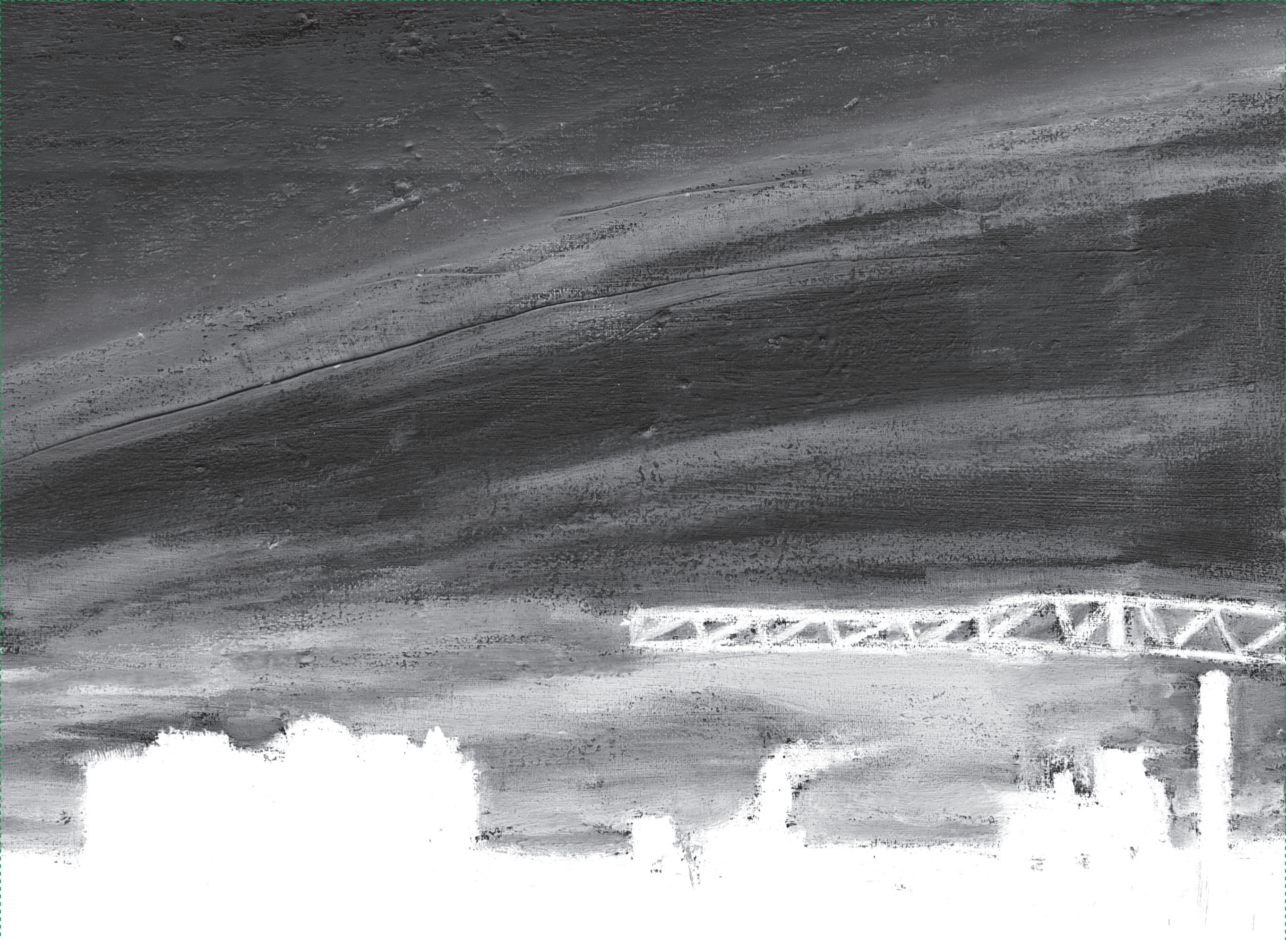


CHAPTER 1

Synthesis

"Most of us take time for granted. Clearly, burglars do not."

(Rengert & Wasilchick, 2000; p. 54)

1.1 Introduction

Criminologists have been studying the questions where and when crimes occur for almost two centuries. Already in the late 1820s, the moral philosophers Guerry and Quetelet investigated crime rates in France (Wortley & Townsley, 2017; pp. 3-4). By creating crime maps for the different French provinces, they showed that crimes cluster across the country in relation to several important socio-demographic features such as poverty and education levels. Another historical root of the early environmental approach in criminology is the establishment of the Chicago School at the beginning of the 20th century. Shaw and McKay, for example, studied the relationship between neighborhood features and delinquency levels in the city of Chicago in the 1930s. They found that those neighborhoods situated in between the city central business district and the more affluent outer zones of the city continued experiencing the highest delinquency rates – even when the population changed (Shaw & McKay, 1969 in Wortley & Townsley, 2017; pp. 4-5). When more closely investigating the residential locations of the juvenile delinquents, Shaw and McKay showed that while most of these juveniles had been replaced by a new generation over the years, new cohorts of juvenile offenders still lived in the same places. Based on this finding it can be concluded that it was not necessarily the person, but mainly the place that influenced levels of delinquency.

The period since the 1970s marks the start of the contemporary environmental criminology approach (Wortley & Townsley, 2017; p. 8). Considerable attention has been paid to the description of a diverse range of spatio-temporal crime patterns, although the emphasis has mostly been on spatial questions (Ruiter, 2017; Wortley & Mazerolle, 2008). Previous spatially-oriented research has focused for example on identifying so-called 'crime hotspots', such as nearby shopping malls, central business districts, sports stadiums and transit hubs (e.g., Chainey & Ratcliffe, 2013; Eck, Chainey, Cameron & Wilson, 2005; Sherman, Gartin & Buerger, 1989; Weisburd, 2015; Weisburd et al., 2016). These places are not necessarily one-time targets. For example, studies have shown that certain places are repeatedly victimized, primarily during the first days and weeks after the initial event took place (e.g., Ashton, Brown, Senior & Pease, 1998; Bowers & Johnson, 2005; Farrell, Phillips & Pease, 1995). In addition, places nearby the initial crime targets are also found to have an increased risk of victimization within a short period of time (e.g., Bowers, Johnson & Pease, 2004; Haberman & Ratcliffe, 2012; Morgan, 2001; Townsley, Homel & Chaseling, 2003).

In recent years, research concerning the question *when* crimes occur has been expanding. This strand of research focuses on what these temporal patterns look like at different temporal scales and how to explain them. So far, most previous studies have focused on the description of seasonality trends (e.g., Andresen & Malleson, 2013; Ceccato, 2005; Linning, Andresen & Brantingham, 2017) or fluctuations in overall crime rates by month of the year (e.g., Ramírez et al., 2016), day of the week (e.g., Andresen & Malleson, 2015; Johnson, Bowers & Pease, 2012; Wheeler, 2016), time of the day (e.g., Felson & Poulsen, 2003; Irvin-Erickson & La Vigne, 2015; Montoya, Junger & Ongena, 2014; Sagovsky & Johnson, 2007) or a combination of these temporal cycles (e.g., Ceccato & Uittenbogaard, 2014; Glasner & Leitner, 2016; Malleson & Andresen, 2015; Van Koppen & Jansen, 1999).

Clearly, these overall spatial and temporal crime patterns are the sum of individual decisions made by offenders. In the end, it is not the target area or the specific time of day that has the agency to make decisions, but the offender who decides on whether, where and when to offend. In order to *explain* the spatio-temporal patterning of crime, we therefore need to make a shift from aggregate-level observations to an individual-level offender perspective. For the aim of the present dissertation, we are not interested in describing where and when crimes occur, but rather in developing and testing explanations for why offenders commit crimes at these specific places and times instead of others. Therefore, the overarching research question is as follows: *How can we explain offenders' spatio-temporal criminal decision-making?*

In trying to answer the overarching research question of this dissertation, we improve upon prior research in environmental criminology in two ways. First, we investigate offenders' *individual* decision-making in a spatio-temporal context rather than studying aggregate-level crime rates. While several ethnographic studies discuss where and at what times individual offenders commit crime (e.g., Cromwell, Olson & Avary, 1991; Rengert & Wasilchick, 2000; Wiles & Costello, 2000; Wright & Decker, 1994), their qualitative interview approaches only enable them to use data of a rather small scale, focusing exclusively on very prolific burglars. The behavior of this specific subgroup may not be generalizable to less prolific burglars, let alone offenders who commit different types of crime. As such, the focus of previous ethnographic research is on describing a few illustrative examples of a specific type of crime in high detail. In contrast, in this dissertation we make use of quantitative analysis of large-scale geocoded and time-stamped police data on repeat offenders of a variety of crime types and the specific dates and times they committed these different types of offenses. In addition, we combine this with the analysis of self-collected data on the spatio-temporal routine activity and crime patterns of a high-risk offender sample using the Time-specific Activity Space (TAS) survey that was specifically designed for this study. Although of a relatively small sample size, our survey-based research design improves upon prior qualitative studies by using a more structured sampling frame, fully-structured questionnaire and a focus on general patterns instead of case to case descriptions.

A second way in which we improve upon prior research is our conceptualization of time. The first manner of looking at time is the passage of time in a *linear* sense (e.g., the duration between a first crime and a second crime). To date, the focus of previous environmental criminology studies has often been on such linear time measures. For example, in the area of (near) repeat victimization research (e.g., Bowers & Johnson, 2005; Haberman & Ratcliffe, 2012; Morgan, 2001), repeat offending is mostly examined with regard to the number of days separating offenses (for two exceptions, see Johnson et al., 2012; Sagovsky & Johnson, 2007). In addition, in almost all crime location choice studies so far that addressed temporal aspects of criminal decision-making (see e.g., Bernasco, 2010; Lammers, Menting, Ruiter & Bernasco, 2015; Menting, Lammers, Ruiter & Bernasco, 2016), the focus is exclusively on these linear time differences (for one exception, see Bernasco, Ruiter & Block, 2017). Lastly, in previous crime linkage analysis studies where series of crimes as belonging to the same offender are identified, the assumption is often made and tested that crimes that happen in close temporal proximity to each other (i.e., in linear time) are more likely to have been committed by the same offender (e.g., Lundrigan & Canter, 2001; Markson, Woodhams & Bond, 2010; Tonkin, Woodhams, Bull, Bond & Palmer, 2011).

However, due to different routine activities and other possible obligations the criminal behavior of offenders is also expected to have cyclically recurring time patterns. This is a second conceptualization of time: the repetition of time in a *cyclical* sense (e.g., the intra-day and intra-week patterning of crime). After all, Mondays usually look very different from, for example, their Saturdays. If an offender has time to commit crime on Saturday afternoon, he might commit another crime on another Saturday afternoon, because the circumstances will be similar again (or at least more similar than at any other time of the day or week). Therefore, throughout this dissertation we investigate the extent to which such cyclical patterns influence the spatial-temporal decision-making of offenders, by studying both offenders' daily routine activity patterns as well as their offending behavior within the day and week. Although the main focus is on cyclical patterns, at some parts of the dissertation we also address linear time patterns (see e.g., Chapter 2). As human mobility research shows that the predictability of individual routines is highest on short time intervals (e.g., Gonzalez, Hidalgo & Barabasi, 2008; Pappalardo et al., 2015; Song, Qu, Blumm & Barabási, 2010), no attention will be paid to seasonal patterns.

1.2 Theoretical framework

Since the 1970s, a number of key environmental criminology theories have been developed, which are aimed at understanding spatio-temporal crime patterns (Wortley & Townsley, 2017). These theories focus on the interactions that occur between an offender and a target at a certain time and place (Brantingham & Brantingham, 1993; Cohen & Felsen, 1979). For the aim of this dissertation, we start the theory section with a description of the individual offender decision-making perspective. Next, we describe the main overarching theory in the field and we argue that this crime pattern theory (Brantingham & Brantingham, 1981; 2008) needs to be extended to make it more time-specific.

1.2.1 Offender decision-making

In order to explain where and when crime events occur, we focus on those with active agency in the criminal decision-making process (i.e., the offenders) and their choices of where and when to commit crime. As the means to achieve goals are limited in terms of time, money and energy, people have to make choices (e.g., Bernasco 2014; Clarke & Cornish, 1985). More specifically, four elements of a choice situation are distinguished in the literature: (1) the decision-maker, (2) the choice alternatives, (3) attributes or characteristics of the choice alternatives, and (4) a decision rule (Ben-Akiva & Bierlaire, 1999). Applied to criminal decision-making, the decision-maker is the offender who decides on where and when to commit crime and the choice alternatives can be spatial (e.g., potential locations at which the crimes can be committed) and temporal (e.g., potential times at which the crimes can be committed). Each of the choice alternatives will be more or less attractive to offenders because of the perceived benefits (e.g., material benefits or symbolic rewards of the crime) and costs involved (e.g., the likelihood of apprehension or obstacles in order to reach a target) (Bernasco & Ruiter 2014, Ruiter 2017).

Given their specific goals, preferences and perception of the situation, offenders are assumed to choose the choice alternatives that bring them closest to their goals in the most cost-effective way (Cornish & Clarke, 2008): those locations and times they expect the rewards of crime to be highest, the risks lowest, and the least effort needed. Note that we do not necessarily assume that all offenders explicitly think and behave in this way. Some of the offenders might consciously weigh the choice alternatives rationally against each other, while others decide more unconsciously or impulsively. The power of decision-making models is that we can analyze the spatio-temporal decision-making behavior of the offenders *as if* they are making such trade-offs (either implicitly or explicitly). This also applies to models from behavioral ecology, such as optimal foraging theory (for an overview, see Vandeviver, Neirynck & Bernasco, 2021). In this model, trade-offs between potential risks and rewards are modelled without the necessity to assume that animals are making these trade-offs consciously.

1.2.2 Crime pattern theory

Crime pattern theory provides a general explanation for why crime patterns are far from random. According to this theory (Brantingham & Brantingham, 1981; 2008), all humans (including offenders) learn about their spatial environment during recurring daily routine activities. It is argued that they develop a so-called 'awareness space', consisting of the activity space (i.e., major routine activity nodes, such as home, school and work, and the travel paths that connect them) and everything within visual range. These activity nodes represent places that offenders visit frequently or where they spend much of their time (Brantingham, Brantingham & Andresen, 2017). As suggested by temporal constraint theory (Ratcliffe, 2006) and based on time geography (Hägerstrand, 1970), these nodes can place strong temporal constraints on offenders which can limit their participation in activities at other places. The core proposition of crime pattern theory, as graphically depicted in Figure 1.1, is that offenders are most likely to commit crime at the intersection of their individual awareness spaces and the spatial distribution of attractive targets. Although the theory is a general theory of crime, opportunity structures are crime-specific. For example, residential burglary opportunities depend on property value and lack of surveillance, while commercial robberies require the presence of businesses and quick access to highways.

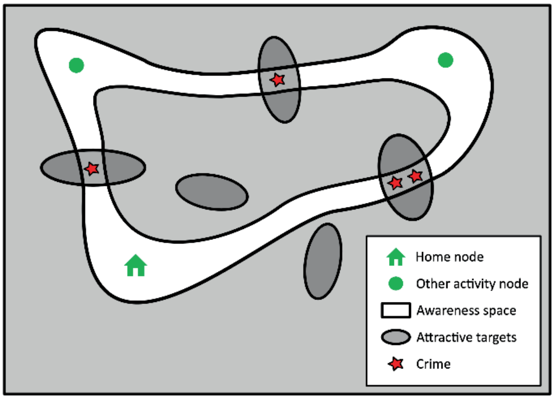


Figure 1.1 Diagram of the central elements from crime pattern theory, adapted from Brantingham & Brantingham (1981, p. 42).

The example offender in Figure 1.1 regularly visits—and travels between—three routine activity nodes (in green), resulting in the white awareness space. All possible attractive target areas for crime, that also have a certain spatial distribution that is not uniform, are shaded dark grey (the dark ellipses). The light gray areas depict the places where the individual awareness space of the offender overlaps with the attractive targets for crime, and the red stars are examples of where the theory predicts the offender commits crime. Because the theory provides an explanation at the individual offender level, the sum of the individual actions of all offenders active in a certain area must in the aggregate lead to the observed spatio-temporal crime patterns mentioned in the introduction. Figure 1.1 represents only one example offender for illustrative purposes, but when overlapping hundreds of these figures macro-level patterns of clustering start to emerge, either because the anchor points of different offenders or attractive targets are located close to each other.

Although the core of crime pattern theory explains spatial patterns in crime, it is also acknowledged that the attractiveness of potential targets is not time stable but rather time-varying over the course of the day and week. An example is given in Figure 1.2. It depicts that the same place can be attractive for an offender during the day, while not so much during the night (e.g., due to varying levels of home occupancy in residential neighborhoods, or the number of cars parked on a parking lot). Therefore, offenders are only expected to commit crime at those places at the times that the targets are attractive (Brantingham et al., 2017).

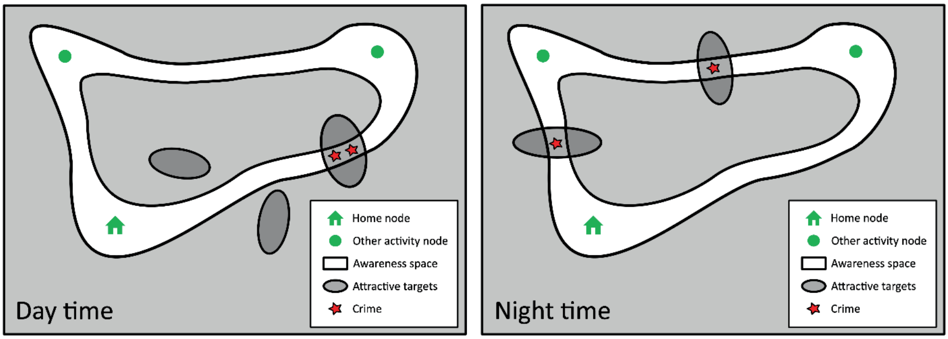


Figure 1.2 Attractive targets are present at different locations during the day (left) and during the night (right), impacting the predicted crime locations at different times of day.

1.2.3 Towards a time-specific theory of crime patterns

In this dissertation, we argue that crime pattern theory to date still has been incomplete. Figure 1.2 only addresses time-varying target attractiveness, but ignores that awareness spaces themselves are time-specific. In fact, the spatial knowledge about criminal risks, rewards and opportunities is acquired during offenders' daily routine activities at specific times of the day and specific days of the week. Part of this time-specific knowledge might be generalizable to other times of day or week using simple heuristics (e.g., information on regular opening and closing hours of supermarkets and shops), while other parts of the knowledge only apply to specific times. Therefore, the *applicability* of the spatial knowledge acquired during daily routines could also be time-varying, which as of yet has not been incorporated in the theory. Instead, all tests of the theory thus far have implicitly assumed a-temporal and time-stable awareness spaces, suggesting that offenders commit offenses in all possible places within their awareness spaces at any time of the day and day of the week, regardless of the times and days they regularly visited these places. In this dissertation, we argue that the acquired knowledge about suitable targets in certain areas is most applicable at the times these areas were previously targeted (see Chapter 4) or routinely visited (see Chapter 5). For example, offenders with a daytime job are generally expected to have more accurate knowledge about suitable targets in the areas surrounding the workplace during 9-5 office hours than what the areas are like at other times of day. In contrast, as drinking areas might generally be visited late at night, we argue that offenders' knowledge about criminal opportunities in these areas mainly applies to the nighttime instead of the daytime.

As displayed in Figure 1.3, we expect not only the locations of attractive targets (i.e., the dark ellipses) but also the applicability of the offender's awareness space (i.e., the white paths) to differ between the daytime and nighttime. Illustrating the travel paths of the example offender in the figure, suppose that the activity node (i.e., the green dot) in the upper right represents the offender's work location and the activity node in the upper left represents an often visited sports location, where his grandmother lives nearby. Leaving the home node in the morning to go to work (see daytime picture in Figure 1.3), the offender follows the path from the home location to the work location in the upper right. During his lunch break at work, the offender follows the path to the upper left for his daily sports activity and returns to the work location afterwards. At the end of the working day, he takes the same route home as how he came to work earlier that day. At night, the offender again leaves the house to visit the same neighborhood where he usually sports during the day to visit his grandmother, but using another travel path (see nighttime picture in Figure 1.3).

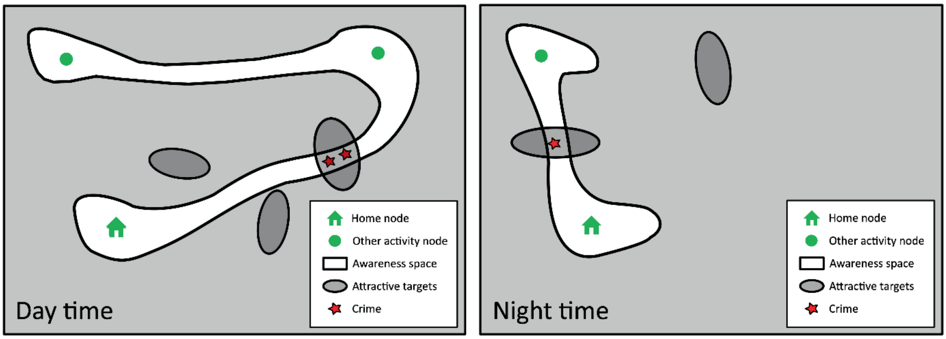


Figure 1.3 Extended crime pattern theory, illustrating the time-varying applicability of spatial knowledge during the day (left) and during the night (right).

Based on the original version of crime pattern theory as depicted in Figure 1.1, we would expect the example offender to have an increased chance of committing crime in four different places (i.e., the red stars). By incorporating time-varying target attractiveness, we expect the offender to commit his crimes at two specific places during the day and two other places during the night (see Figure 1.2). However, based on our time-specific crime pattern theory that includes time-varying applicability of spatial knowledge as well as time-varying target attractiveness (see Figure 1.3), we expect the offender to have a higher chance to commit crime at only one place during the night (instead of two) – as his acquired spatial knowledge is less applicable to the other place at nighttime. In other words, our extended version of crime pattern theory leads to other predictions than the original theory, in this example the absence of the red star in the middle above.

As argued before, the offender might of course also use simple heuristics to generalize the time-specific knowledge to other times. Nevertheless, the spatial knowledge about a certain area gained at a specific time is more accurate by directly observing it during routine visits than a generalization based on heuristics and therefore best applicable to what the situation would look like around that time of day. As both the applicability of offenders' awareness spaces and the distribution of criminal opportunities (i.e., the two necessary conditions for a crime to be committed) are independently of each other time-varying, they can also be studied separately of each other. The focus of this dissertation is on the time-varying awareness spaces of offenders.

1.3 Data sources

In order to better understand offenders' spatio-temporal criminal decision-making and to provide first tests of our time-specific extension of crime pattern theory, an ideal dataset would have large-scale information on both offenders who got caught and those unknown to the police about (1) where and when they committed offenses, as well as (2) their daily routine activities. This implies that we would need a dataset in which the locations and times are accurately measured, not only for the crimes but also with regard to the offenders' routine activity patterns. Unfortunately, such data do not exist and we therefore decided to use multiple data sources that still allow us to address the overarching research question and test our hypotheses even though our data sources have some shortcomings. In the remainder of this section, we will discuss each of the two primary data sources used in this dissertation in more detail and describe to what extent they meet the necessary requirements to answer our central research question.

1.3.1 Large-scale geocoded and time-stamped police data

The Netherlands keeps large-scale crime statistics and the Dutch law on police data explicitly states that it is allowed to use these data for scientific research. For Chapter 2 and Chapter 4 of this dissertation, we were able to obtain suspect data from the Dutch Suspect Identification System used by The Hague Police Service, including information on the specific date, time and type of their offenses. Although all suspects in our data were charged with a crime and the cases were submitted to the public prosecutor's office, they were not necessarily all convicted. In general, approximately 90 percent of the cases are at a later stage either settled by the public prosecutor or the suspects are found guilty in a criminal court (Besjes & Van Gaalen 2008, Blom, Oudhof, Bijl & Bakker, 2005).

In our large-scale police dataset, we used both the locations and timing of the reported crimes. With regard to the spatial measurement, we geocoded the longitude and latitude information on all the crime locations (as well as on the offenders' home locations) to one of the 142 neighborhoods in the greater The Hague area in the Netherlands. Regarding the temporal measures, the police reported the time frames in which the crime must have been committed, as is common practice in many jurisdictions. Although these 'start and end times' were similar for the majority of the crimes, there were still quite some cases (e.g., about one-fifth of the offenses in Chapter 4) where the exact timing of the offense could not accurately be reported due to multiple reasons. These time windows were ranging from small differences within the hour to larger differences within the week. For all our analyses in Chapter 2 and

Chapter 4, we used the end times of the crimes. We expect these times to yield the most reliable information because a crime event can only be reported *after* its commission. For example, suppose a couple gets home after performing a certain activity during the day to discover their home was burglarized. We expect that at that moment they will watch the clock and quite precisely remember the time they got home, while their knowledge about the specific time they left the home earlier that day might be less accurate. We performed additional robustness checks by either using the start times or the midpoint between the start and end times (Chapter 2), or by using a subsample of the offenses for which the exact times were recorded (Chapter 4).

For the study of time-specific crime location choices in Chapter 4, we supplemented the offender data from the police with three additional register data sources: (1) measures of offenders' current and past residential locations from the Dutch information system on residential addresses, (2) demographic and socioeconomic neighborhood characteristics from Statistics Netherlands, and (3) on the locations of a variety of businesses and facilities from the Dutch LISA data. Using (part of) these large-scale register data, we were able to study the extent to which repeat offenders commit their crimes at similar hours of day and similar hours of week (see Chapter 2) and the extent to which they are more likely to return to previously targeted areas at similar days of the week and times of the day (see Chapter 4).

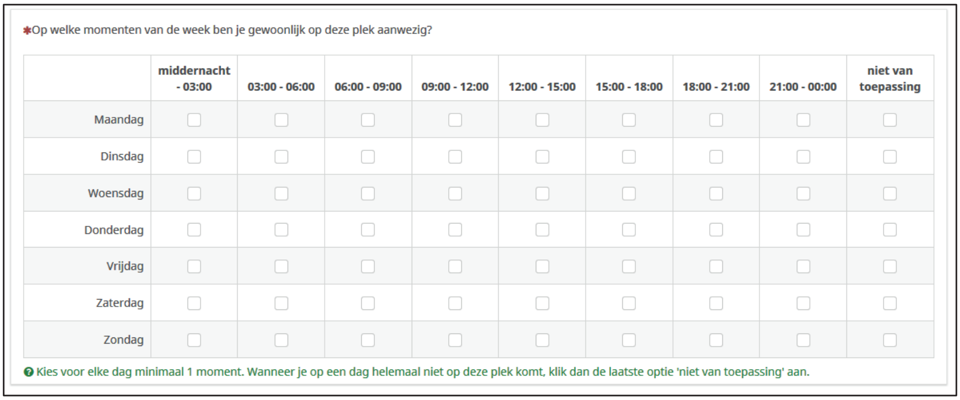
1.3.2 Data collection using the Time-specific Activity Space (TAS) survey

While the large-scale dataset from the Dutch police has the advantage of providing information on a large group of offenders and the times and locations of their offense histories, this data source generally contains very limited information on offenders' individual activity spaces (Ruiter, 2017). Often only the offenders' previous offense locations (e.g., Kuralarasan & Bernasco, 2021; Lammers et al., 2015; Long, Liu, Feng, Zhou & Jing, 2018) and their current home addresses (e.g., Bernasco & Nieuwbeerta, 2005; Townsley & Sidebottom, 2010) are known. In a few recent studies, the existing police data have been supplemented with information on additional activity nodes, such as the home locations of close family members (e.g., Curtis-Ham, Bernasco, Medvedev & Polaschek, 2021; Menting et al., 2016), or new data have been collected on activity nodes such as schools, workplaces and leisure activities of offenders (e.g., Menting, Lammers, Ruiter & Bernasco, 2020). Other studies have used proxy measures to predict activity spaces, such as by using graph theory metrics on the street network (e.g., Frith, Johnson & Fry, 2017). Unfortunately, these studies did not measure when the offenders committed their crimes nor at what times of day these places were routinely visited by the offender. Therefore, for Chapter 3 and Chapter 5 of this dissertation, we designed an online survey which we conducted among a high risk sample of 363 respondents in the Netherlands.

In this Time-specific Activity Space (TAS) survey, we asked the respondents to extensively report on their most important routine activity nodes of the past year, categorized in seven different domains: (1) homes, (2) schools, (3) jobs, (4) sports activities, (5) shopping, (6) going out, and (7) any other activities. For each domain, we asked the respondents to indicate the locations of a maximum of six current and past activity nodes that they visited approximately every week over the past year. We used the Google Maps functionality included in the LimeSurvey platform to which we added an interactive search bar ("Zoek…") to help respondents locate their activity nodes (see Figure 1.4).

Figure 1.4 Google Maps functionality with interactive search bar included in the TAS survey.

In addition, the respondents were asked on which days of the week and which times of the day they had usually visited each of these locations in the past year. For each day, we presented the respondents with eight possible time slots of three hours each, starting from midnight-3 a.m. and ending at 9 p.m.-midnight (see Figure 1.5). Lastly, we asked the respondents in the survey at which locations and times they had committed a crime in the past year, across a range of seven different crime types: (1) residential burglary, (2) theft of/from a bicycle, car or other (motor) vehicle, (3) theft from a shop/shoplifting, (4) theft (of an object) from a person, (5) robbery, (6) assault, and (7) vandalism. Of the 363 respondents that fully completed the online questionnaire, 30 reported to have committed at least one crime in the year prior to the survey (71 unique crimes in total).



*Op welke momenten van de week ben je gewoonlijk op deze plek aanwezig?

	middernacht - 03:00	03:00 - 06:00	06:00 - 09:00	09:00 - 12:00	12:00 - 15:00	15:00 - 18:00	18:00 - 21:00	21:00 - 00:00	niet van toepassing
Maandag	☐	☐	☐	☐	☐	☐	☐	☐	☐
Dinsdag	☐	☐	☐	☐	☐	☐	☐	☐	☐
Woensdag	☐	☐	☐	☐	☐	☐	☐	☐	☐
Donderdag	☐	☐	☐	☐	☐	☐	☐	☐	☐
Vrijdag	☐	☐	☐	☐	☐	☐	☐	☐	☐
Zaterdag	☐	☐	☐	☐	☐	☐	☐	☐	☐
Zondag	☐	☐	☐	☐	☐	☐	☐	☐	☐

Kies voor elke dag minimaal 1 moment. Wanneer je op een dag helemaal niet op deze plek komt, klik dan de laatste optie 'niet van toepassing' aan.

Figure 1.5 Week calendar of seven days of the week multiplied by eight 3-hour time slots included in the TAS survey.

Note: rows refer to days of the week; columns to a 3-hour time slot; the final column "not applicable" was offered as a quick way to indicate that the particular activity node was never visited on that particular day.

We anticipated beforehand that not all offenders would indicate the locations and the times they routinely visited with the same degree of accuracy. Therefore, we also included several questions about the spatial and temporal accuracy in the survey to be able to check and compare the reported accuracy levels for the different routine activity domains and the different types of crime. Respondents reported the timing of their routine and criminal activities over the days of the week and time slots of the day to be "reasonably accurate" or "very accurate" for more than eighty percent of the reported times in the survey. For the exclusively temporal analysis in Chapter 3, we made use of the original 3-hour time slices from the online questionnaire (ranging from midnight-3 a.m. to 9 p.m.-midnight): seven days of the week comprising each of eight different 3-hour time slots, for 7*8 = 56 time slots to be analyzed in total.

For the spatio-temporal analysis in Chapter 5, we observed that most activity locations were visited during multiple 3-hour time slots. This high degree of overlap in activities between the eight different 3-hour time slots resulted in too many neighborhoods that were routinely visited at both the same and different time slot of the day as the crime event (instead of only at the same time or only at a different time) to perform the analysis. For the analysis of Chapter 5, we therefore divided the time of day category into the two most distinct time blocks: daytime (6 a.m.-6 p.m.) and nighttime (6 p.m.-6 a.m.). This offered a less detailed temporal granularity than was possible for the exclusively temporal analysis in Chapter 3. With regards to the spatial accuracy, three-quarters of the activity node and crime locations were indicated to be accurate to the neighborhood level or smaller. It was therefore safe to use neighborhoods as spatial unit of analysis in Chapter 5. For this chapter, we geocoded the longitude-latitude information from the online survey to one of the 13,305 unique neighborhoods in the Netherlands for the year 2018.

Overall, the use of our online survey instrument has a great advantage over previous register based studies, as we included a much wider range of the relevant routine activity nodes in offenders' activity spaces, as well as the time of day offenders usually visited these activity nodes, than usually used in those studies. As such, we were able to study the extent to which offenders are less likely to commit their crimes at times when they are routinely engaged in a non-discretionary activity as compared to times when they are routinely engaged in a discretionary activity (see Chapter 3) and the extent to which they commit their crimes in areas they have regularly visited at the same time of day versus areas they regularly visited at different times of the day (see Chapter 5).

1.4 Overview of the empirical chapters

In this section, we discuss each of the four remaining chapters of this dissertation in more detail[1]. Before describing the main research questions, hypotheses, methods and empirical findings per chapter, we first start with some background of how the different studies came into being and how they are related. The overall aim of this dissertation is to explain offenders' spatio-temporal criminal decision-making behavior. To date, both crime pattern theory and related empirical research in environmental criminology have been mainly concerned with offenders' choices of where to commit crime, but have barely addressed the timing of those spatial choices (as in Figure 1.3), let alone offenders' choices of when to commit their crimes. As such, previous research implicitly assumed that offenders are equally aware of criminal opportunities at different times of the day and different days of the week and are therefore equally likely to commit offenses at any time and day in all possible places within their awareness spaces. This dissertation challenges this unrealistic assumption by improving current theory and rigorously testing hypotheses derived from the improved theory using a combination of already existing and newly collected data sources.

As a first step in answering the overarching research question, we start in Chapter 2 with the examination of people who have been suspected of committing at least two crimes and use the crime histories of these repeat offenders to investigate the degree of temporal consistency in individual offending patterns: whether they commit their crimes at similar times of the day and week. In order to filter out the temporal consistency that can be attributed to time-varying attractiveness of potential targets and shared time-use patterns across offenders from the overall level of temporal consistency observed in our data, we developed a Monte Carlo permutation test. In the third chapter of this dissertation, we use the discrete choice model (see e.g., Bernasco & Ruiter, 2014; Ruiter 2017) to explain offenders' temporal decisions and study the role of both discretionary and non-discretionary routine activities in the criminal decision-making process. The crime time choices of offenders and the question why they commit their crimes at these times and not others have to date remained rather under-studied in the literature. In this chapter, we estimate a conditional logit model as commonly applied in crime location choice research, but with a temporal rather than a spatial choice set (see Chapter 3). In the last two chapters of this dissertation, we put our extended crime pattern theory (see paragraph 1.2.3) to the test. In

[1] The empirical chapters of this dissertation have been written as individual manuscripts, which have either been published or submitted to scientific journals. This results in some overlap (e.g., introducing crime pattern theory or discussing the Time-specific Activity Space survey) and stylistic inconsistencies of tables and figures that could not be avoided.

order to test the novel idea of time-varying applicability of offenders' awareness spaces, we use the discrete choice modeling approach and try to explain the crime location choices of offenders by looking at the influence of several temporal factors: returning to previously targeted areas at similar times of the day or similar days of the week (see Chapter 4) and committing crime in routinely visited areas at specific times of the day (see Chapter 5). We next discuss the empirical chapters of this dissertation in more detail.

1.4.1 When do offenders commit crime? An analysis of temporal consistency in individual offending patterns

While many offenders only commit one crime (that the police know about), some offenders commit multiple crimes during the course of their criminal career. Previous research has already shown that such repeat offenders are very consistent in *where* they commit offenses, for example with regard to their routinely visited places, the travel direction from home and the distance from their homes to the crime locations (e.g., Menting et al., 2020; Townsley & Sidebottom, 2010; Van Daele & Bernasco, 2012). However, it is unknown whether offenders also repeatedly commit offenses at a similar *time* of day or day of the week. Human mobility research shows that routine activities clearly differ from one person to the next, but individual patterns show strong recurring daily and weekly rhythms (e.g., Gonzalez et al., 2008; Pappalardo et al., 2015; Song et al., 2010). Because offenders, victims and potential guardians are all subject to temporal constraints in their daily time budget due to important routine activities, in Chapter 2 we argue that offenders show consistency in the timing of their offending and thus commit their crimes at approximately the same times of day and days of the week. For example, an offender who committed his first offense on Monday afternoon is more likely to commit his second offense again on Monday afternoon. For another offender who has committed his first offense on Saturday night, we expect him to be more likely to commit his second offense again on Saturday night than on some other day and time. Therefore, the research question of this chapter states: *To what extent do repeat offenders commit their crimes at similar hours of day and similar hours of week*?

Using large-scale time-stamped police data (see paragraph 1.3.1 for more details), we analyze the offense histories of 28,274 repeat offenders who committed a total of 152,180 offenses between 1996-2009 in the greater The Hague area of the Netherlands. One challenge in this chapter is that we know from the discussion on crime pattern theory that target attractiveness changes over the course of the day and the week (see Figure 1.2). For example, homes are more attractive for residential burglary when residents are away during the day.

During weekends and especially in the evening, entertainment areas are quite attractive for pickpocketing, while those areas might well be deserted on weekdays. As we want to quantify the extent to which the same offenders commit crimes on the same days and at the same times, we have to filter out the effect of time-varying attractiveness of suitable targets and similarities in inter-offender time-use patterns. We developed a Monte Carlo permutation procedure to test whether repeat offenders commit their crimes at similar hours of day and week (i.e., intra-offender temporal consistency) *over and above* what is to be expected based on the overall temporal distribution of crime events in the data.

The results reveal that repeat offenders show strong temporal consistency in offending: they commit their crimes at more similar hours of the day and more similar hours of the week than is to be expected given the overall temporal distribution of crime. In addition, the observed temporal consistency patterns are stronger for offenses of the same type of crime than for offenses of different crime types. The temporal consistency patterns are also found to be stronger the shorter the time span between the offenses. We can conclude that while previous studies already showed that offenders are consistent in their spatial criminal decision-making, the present article shows that they also make consistent temporal crime choices. This study also highlights the importance of considering the number of offenses committed by the offenders. Unlike repeat offenders who only commit a few crimes and appear to do those few crimes primarily at similar times of the day and days of the week, very prolific offenders do not have such a clear temporal offending pattern.

1.4.2 Crime time choice: the role of discretionary and non-discretionary routine activities in temporal criminal decision-making

In Chapter 3 we try to explain the temporal consistency patterns found in Chapter 2. To date, the question *why* offenders commit their crimes at certain times instead of others has remained rather under-studied in the environmental criminology literature. As routine activities can place strong temporal constraints on humans and hence offenders, they can set boundaries for participation in other activities, such as committing crime, during certain time periods (Golledge & Stimson, 1997; Hägerstrand, 1970). Although several ethnographic studies already reported on offenders' routine activity patterns in relation to their criminal behavior, these studies were limited to small-scale interviews with professional burglars only. Therefore, in this chapter we systematically combine offenders' crime time choices with a detailed account of their temporal routine activity patterns. We examine the relationship between these activity patterns and the timing of offenders' crimes by making a distinction between discretionary routine activities that are voluntary or less time-compulsory (e.g., shopping or going out) and non-discretionary routine activities that generally have more rigid time windows in which they need to be performed (e.g., going to work or attending school). We hypothesize that the discretionary nature of these former activities allows more flexibility to change plans and commit crime instead. The research question of this chapter reads: *To what extent are offenders less likely to commit crime at times when they are routinely engaged in a non-discretionary activity than at times when they are routinely engaged in a discretionary activity?*

To test our hypotheses, we use the Time-specific Activity Space (TAS) survey we developed (see paragraph 1.3.2 for more details). The survey collected information on the specific times of day offenders routinely visited a wide range of both non-discretionary activities (i.e., the domains of work and education) and discretionary activities (i.e., the domains of home, sports, shopping, going out and other activity). Whereas most studies that applied the discrete choice model in environmental criminology after Bernasco and Nieuwbeerta (2005) focused on spatial choices (including the body of this dissertation, see Chapter 4 and Chapter 5), in this chapter the focus is on the *temporal* criminal decision-making of offenders: the choice outcome is a 3-hour time slot out of the 56 possible time slots in the week. Contrary to our expectations, we were not able to show that offenders are less likely to commit crime at times when they were usually engaged in routine activities as compared to the times when they were not, nor that they were less likely to commit crime at times when they were routinely engaged in non-discretionary activities than at times when they were routinely engaged in discretionary activities.

To our knowledge this is the first study in environmental criminology that systematically combines offenders' crime time choices with a detailed account of their temporal routine activity patterns. While spatial location choice studies have consistently shown that the locations offenders regularly visit are predictive of where they commit crime, we do not find evidence for the expectation that the times they are usually engaged in (non-)discretionary routine activities are predictive of the specific times of day they commit their crimes.

1.4.3 A time for a crime: temporal aspects of repeat offenders' crime location choices

Criminologists have found that certain targets have a higher chance of being victimized on multiple occasions. This finding is often explained by a tendency of offenders to return to a previously targeted area because they were successful there in the past. Previous studies have indeed shown that offenders are more likely to commit crime in previously targeted areas than in areas they never targeted before (e.g., Bernasco, Johnson & Ruiter, 2015; Long et al., 2018).

Building on this literature, we take our extended crime pattern theory to a first empirical test in Chapter 4, but only with regard to the idea that the previous crime location (instead of the broader awareness space as depicted in Figure 1.3) at a certain time is informative for the next crime. More specifically, we examine the relationship between returning to previously targeted areas and the timing of one's crimes. We expect that when offenders learn about criminal opportunities from prior offenses, their knowledge about the attractiveness of these previously targeted areas might not apply equally to all situations as the potential risks and rewards involved during the day differ from those during the night. This, in turn, is expected to influence the locations where the offenders subsequently choose to offend. This chapter's research question reads: *To what extent are repeat offenders' crime location choices conditional on the timing of the offenses within the week and within the day?*

Police data on 12,639 offenses committed by 3,666 repeat offenders in the Netherlands are analyzed using discrete spatial choice models, that allow us to simultaneously study the impact of both target and offender characteristics on criminal target selection (e.g., Bernasco & Nieuwbeerta, 2005; Ruiter, 2017). The individual decision-maker is the offender and the dependent variable is the spatial choice outcome: the alternative (i.e.., the neighborhood where the crime is committed) the offender has selected from a countable set of alternative locations (i.e. all neighborhoods where the crime could have been committed). In line with previous studies, we show that offenders are more likely to commit crime in previously targeted neighborhoods than elsewhere. Regarding our temporal hypotheses, we find that the likelihood to commit crime in previously targeted neighborhoods is 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 neighborhood during different parts of the week and different times of day. Particularly, repeat offenders are most likely to offend in neighborhoods they already targeted before on the exact same weekend day or weekday with only a 0- to 2-hour difference between the offense times. Moreover, the effects are stronger for offenses of the same type of crime than for different types of offenses.

These findings provide support for our extended crime pattern theory. We hypothesized that the applicability of spatial knowledge in offenders' awareness spaces (operationalized as previous crime locations) differs over the day and week. Based on this study, we can conclude that offenders are much more likely to return to previously targeted neighborhoods when committing the offense at a similar day of the week or similar time of the day compared to a different day or time. For a better understanding of offenders' spatial criminal decision-making, both offenders' previous crime locations and their timing within the day and within the week need to be taken into account in future research. In addition, the findings suggest that the term awareness space needs an even more dynamic conceptualization than the extended version as proposed by Bernasco (2010). While he acknowledged the effects of time passing on spatial knowledge, in section 1.1 we suggested that not only such linear but also cyclical time patterns should be incorporated in the theory.

1.4.4 Right place, right time? Making crime pattern theory time-specific

In Chapter 5, we broaden the scope of the crime location choice research performed in Chapter 4. We examine not only offenders' home and previous offense locations as important—and commonly available in police data—anchor points in offenders' awareness spaces, but also a variety of other routine activity nodes. In Chapter 4, we already argued that repeat offenders develop time-specific knowledge of their crime locations and are therefore more likely to return to previously targeted areas at the same time of day or at the same day of week. In Chapter 5, we generalize this idea to all offenders and other routine activity nodes by reconceptualising the awareness space concept itself. Building on our extended crime pattern theory as discussed in paragraph 1.2.3, we posit that the applicability of spatial knowledge across the *entire* awareness space is time-specific (see Figure 1.3), not only for previous crime locations. This implies that the acquired knowledge of suitable targets in certain areas is most applicable at the times these areas were visited by the offenders during their daily routine activities (regardless of whether they had committed crime in these areas). As graphically displayed in Figure 1.3, our extended version of crime pattern theory therefore leads to other predictions than the original theory that only incorporated time-varying target attractiveness. The research question in the final chapter of the dissertation reads: *To what extent do offenders commit crime in areas they have regularly visited at the same time of the day compared to areas they have regularly visited at different times of the day?*

In this final chapter, we use the Time-specific Activity Space (TAS) survey we developed (see paragraph 1.3.2 for more details). This enables us to study a wider range of routine activity nodes that more closely matches the concept of awareness spaces, such as school, work and a variety of different leisure activities. We examine the specific times of day a group of 30 offenders regularly visited their most important activity nodes as well as the timing and location of their self-reported 71 offenses over the past year. The results of the discrete spatial choice model suggest that offenders are indeed more likely to commit crime in neighborhoods they regularly visited at the same time of the day than in neighborhoods they regularly visited at different times of day – though the effect size difference was not statistically significant in our small sample.

Based on the findings of this study, we can conclude that our extension of crime pattern theory is only tentatively supported. We hypothesized that offenders' awareness spaces are not only spatially varying as suggested by the original crime pattern theory, but also that their applicability is temporally varying – due to the fact that people visit routine activity nodes at certain times of day and thus acquire knowledge about the locations of attractive targets that is best reflective of those times. The results of this final chapter indeed suggest that not only offenders' previously targeted neighborhoods (as examined in Chapter 4), but also neighborhoods they had regularly visited before have an increased risk of being targeted at similar times of the day.

1.5 Discussion

This dissertation builds on theoretical and empirical studies in the area of environmental criminology trying to explain offenders' spatio-temporal criminal decision-making. Table 1.1 provides a schematic overview of the main research questions, data sources and empirical approaches used in Chapter 2 to Chapter 5. In order to answer the overarching research question of this dissertation, we used several research methods throughout the chapters: a newly developed Monte Carlo permutation test (Chapter 2), a discrete temporal choice model (Chapter 3) and two discrete spatial choice models with temporal variables included (Chapter 4 and Chapter 5). Based on the empirical findings of these studies, we can draw four overall conclusions which will be discussed in more detail below. This final section then continues with a discussion of the limitations and avenues for future research, and we end with discussing the implications for law enforcement and criminal justice responses to crime.

Chapter	Research question	Crime data source	Empirical approach
2	To what extent do repeat offenders commit their crimes at similar hours of day and similar hours of week?	Large-scale geocoded and time-stamped police data	Monte Carlo permutation test
3	To what extent are offenders less likely to commit crime at times when they are routinely engaged in a non-discretionary activity than at times when they are routinely engaged in a discretionary activity?	Time-specific Activity Space (TAS) survey	Discrete temporal choice model
4	To what extent are repeat offenders' crime location choices conditional on the timing of the offenses within the week and within the day?	Large-scale geocoded and time-stamped police data + contextual data sources	Discrete spatial choice model
5	To what extent do offenders commit crime in areas they have regularly visited at the same time of the day compared to areas they regularly visited at different times of the day?	Time-specific Activity Space (TAS) survey	Discrete spatial choice model

Table 1.1 Overview of the research questions, data sources and empirical approaches per chapter.

1.5.1 Overall conclusions

A first overall conclusion is that offenders' awareness spaces should no longer be conceptualized as time-invariant in crime pattern theory. According to this theory (Brantingham et al., 2017), offenders commit crime at those places where their individual awareness spaces overlap with the spatial distribution of attractive targets. Both the theory and related empirical research in environmental criminology have to date remained rather *a-temporal*, as if the timing of offenders' routine activities and their crimes plays no role. This dissertation improves the original crime pattern theory and proposes a time-specific extension: offenders' spatial knowledge acquired during daily routine activities is not equally applicable to all times of day or week, which influences the locations where they subsequently choose to offend (see Figure 1.3). Based on the results of Chapter 4 and Chapter 5, we can conclude that offenders' knowledge of a neighborhood at a particular time acquired by committing previous crimes in that neighborhood (as shown in Chapter 4) or by visiting routine activity nodes in that neighborhood (as shown in Chapter 5) is related to the commission of crime around that same time. The acquired knowledge of time-constant characteristics will of course apply regardless of the specific time of day, and part of the knowledge that relates to time-varying features might also be generalizable to other times using simple heuristics. For example, although an offender might visit certain routine activity nodes exclusively during the day, he might still be able to make good estimations about what the situation would be like at night (e.g., based on regular opening and closing hours). Chapter 5 indeed shows that while routinely visiting neighborhoods at certain times of day provide offenders with spatial knowledge that is best applicable to these specific times, it is still somewhat predictive for offenders' crime location choices at different times.

A second conclusion of this dissertation is that offenders are quite consistent in their temporal criminal decision-making. Previous research already showed that repeat offenders are very consistent in where they commit offenses, such as regarding their routinely visited places, the distance from their homes to the crime locations and the travel direction from home. Chapter 2 shows that repeat offenders also display strong temporal consistency in their individual offending behavior: they repeatedly commit crime at similar hours of the day and similar hours of the week over and above what is to be expected from the overall temporal crime pattern. For example, an offender who commits a first offense on Wednesday afternoon is more likely to commit his second offense again on a Wednesday afternoon, compared to, for example, a Friday or Saturday evening. This way, we move forward in increasing our understanding of the temporal crime clusters on the macro-level introduced in the introduction of this dissertation:

many crimes are observed on certain 'hot' days and times not only because attractive targets and shared time-use patterns across offenders converge at those days and times, but also because individual offenders are rather consistent in their temporal offending behavior on the micro-level. This intra-offender temporal consistency may contribute to create clusters of 'hot' crime times on the aggregate level, as many offenders commit their crimes at the same day and time.

A third overall conclusion is that offenders' crime location choices are influenced by several temporal factors. The results of the discrete spatial choice model in Chapter 4 suggest that the likelihood to commit crime in previously targeted areas is much stronger when a repeat offender had committed the previous offense during similar parts of the week or similar times of the day than when he or she previously targeted the area at different parts of the week or day. Using detailed information on offenders' spatio-temporal routine activity and crime patterns collected through the TAS survey, the results of Chapter 5 shows that not only *previously targeted* areas are at increased risk of being targeted at similar times, but also areas they had *regularly visited* before at the same time of the day. Recall from the introduction that the overall spatio-temporal crime patterns observed on the aggregate level are the sum of individual decisions made by offenders on whether, where and when to offend. Because the macro-level itself has no agency, it was argued that individual-level offender decision-making should be studied. Future research could therefore use the micro-mechanisms shown in Chapter 4 and Chapter 5 of this dissertation to arrive at macro-level predictions about the overall spatial and temporal patterns in crime.

A final conclusion of this dissertation is that offenders' spatio-temporal patterns of criminal decision-making vary by type and recency of the offenses. As both routine activity patterns and opportunity structures change over the life course, we expect the strongest temporal patterns within the day and week when offenses are committed shortly after one another and less so when the offenses are a long time apart. The results of Chapter 2 show that this is indeed the case regarding our measure of temporal consistency in individual offending patterns: the consistency patterns of the repeat offenders in our data were found to be stronger the shorter the time span between their offenses, especially with regard to offenses that were committed within one month. Also, although our time-specific crime pattern theory provides a general explanation for where and when offenders commit their crimes, opportunity structures clearly vary for different crime types. This means that different types of crime also require different knowledge about the time-varying attractiveness of potential targets (i.e., "crime-specific time-specific knowledge"). For example, although home occupancy is a relevant factor for residential burglary, this time-specific knowledge is less useful for committing another type of crime with a completely different opportunity structure. In this dissertation, we find that offenders' temporal consistency patterns (Chapter 2) and the likelihood that they return to previously targeted areas at similar tikes (Chapter 4) are indeed stronger for offenses of the same type of crime than for offenses of a different crime type.

1.5.2 Limitations and avenues for future research

A few important caveats and avenues for future research need to be mentioned. First, throughout the dissertation we only focus on single offenders with their isolated crime histories and activity spaces, while in fact co-offending is a common phenomenon (e.g., Bernasco, 2006; Lammers, 2018). Specifically, all offenses in the four empirical chapters are treated as if they were committed by one single offender. In reality, however, co-offenders could also have been involved with some of the crimes under study, which means that the routine activity patterns of different offenders—instead of only one offender—are at play (see Lammers, 2018). We would expect, for example, that the temporal consistency effects found in Chapter 2 are even larger among purely solo-offenders than in the mixed offender group from the police data used for this chapter. However, the fact that co-offending implies a mixture of offender routines might further complicate the analyses performed in the different chapters of this dissertation, as well as future research on this topic.

Second, we only analyze the behavior of offenders that were known to the police. Although the macro-level crime patterns contain both solved and unsolved crimes, we have to acknowledge that the datasets used in this dissertation capture only a specific subgroup of offenders (i.e., those that were suspected of a crime). As such, our conclusions are only generalizable to the total offender population to the extent that caught offenders are similar to offenders that are not caught by the police. The few studies that compared the offending patterns of suspected and non-suspected offenders were not able to find evidence for differences in spatial offending or patterns of temporal decay (e.g., Johnson, Summers & Pease, 2009; Lammers, 2014; Summers, Johnson & Rengert, 2010). However, these studies did not take the routine activity patterns of offenders and timing of their crimes within the day and week (i.e., cyclical time patterns) into account. Therefore, a next step forward for future studies is to also investigate the routine activity spaces of offenders that have not been arrested by police as well as their spatio-temporal decision-making. This might be done, for example, by selecting survey samples of (active) offenders that can report on both their solved and unsolved offenses.

Third, with our Time-specific *Activity Space* survey we are not able to fully capture the concept of offenders' awareness spaces. Although the routinely travelled paths between activity nodes are present in Figures 1.1 to 1.3, by not including them in the empirical design we make the implicit assumption that offenders are 'teleported' between activity nodes during the course of a day. In Chapter 5 we make a first step in addressing this shortcoming by modelling first-, second- and third-order spatial lags around the neighborhoods of offenders' activity nodes. However, by including all the adjacent neighborhoods these lags cover all directions, instead of the specific routes taken by the offenders between their most important activity nodes. In future studies, our empirical analyses could be extended by predicting the plausible travel paths between the different activity nodes (for example using a shortest-path algorithm) or by measuring the actual travel paths (for example, using smartphone applications or other type of GPS-tracking to capture both the activity nodes and the paths that connect them, see e.g., Rossmo, Lu & Fang, 2012; Ruiter & Bernasco, 2018). Knowing more about the (most likely) travel behavior of individual offenders is important, as it might, for example, help in explaining why they commit their crimes in certain places that are *not* close to their routine activity nodes. We suggest that future research will find that these places are most likely located on a routinely travelled path between activity nodes.

A fourth limitation of this dissertation is that we have no information about within time slot heterogeneity in our TAS survey. While more than one-third of the 71 offenses are committed at a 3-hour time slot in which the offenders reported being routinely engaged in multiple activities, the temporal resolution of the data does not enable us to look at a smaller temporal scale than these 3-hour time slots. For example, when a respondent indicates in the questionnaire to have routinely spent time on both shopping and exercising at a specific 3-hour time slot, does he do his groceries before or on the way to back to the sports center? In fact, many different things can happen in a 3-hour time slot and this temporal resolution used may have led to erroneous assumptions that a crime was committed during a routine activity rather than before or after within the general 3-hour period. In addition, our measurement is about offenders' average routine behavior over the past year (i.e., the time spent at routine activity nodes that the offenders visited approximately every week) instead of the specific activities involved around the time of the actual crime. This results in a disconnect between the theoretical expectations and empirical design in Chapter 3. We therefore cannot make a 1-to-1 link between offenders' crime time choices and their involvement in (non-)discretionary routine activities in this chapter.

Fifth, in testing our extended version of crime pattern theory this dissertation mainly focuses on one of the two necessary conditions for a crime to be committed. Recall that offenders commit crime at locations where the attractive crime opportunities overlap with their personal awareness spaces. In both Chapter 4 and Chapter 5, we paid a lot of attention to the reconceptualization of offenders' time-specific awareness spaces. However, as displayed in Figure 1.2, opportunities for crime are obviously also time-specific and these vary by crime type. In Chapter 2, we already made a first attempt of addressing this issue by filtering out the time-varying attractiveness of potential targets from the overall level of temporal consistency observed in our data. In Chapter 4, we included several important target area characteristics in our analysis, but these were a-temporal. Future research should therefore focus on time-specific characteristics of target locations and more closely investigate specific crime types with their time-varying attractiveness. For example, residential burglars are not likely to enter a home when the residents or neighbors are present (see e.g., Cromwell et al., 1991; Rengert & Wasilchick, 2000). Thus, to understand residential burglary, data are needed about the number of people present in residential neighborhoods (or households) at certain times of the day, which could be approximated by calculating the percentage of employed persons per household in residential neighborhoods (see e.g., Boivin & Felson, 2018). In contrast, shoplifters are not deterred by the presence of home residents, but rather consider the opening hours of shops and the number of people present (who could witness their crime or intervene, but could also provide anonymity). Lastly, to examine the time-varying target attractiveness for other types of property crime, future research might also consider carrying out systematic observations to determine variations in the number of bicycles and motor vehicles (for bike or car theft) or the number of people in a given area (for pickpocketing or robbery).

A final limitation of this dissertation is that in our attempt to explain offenders' spatio-temporal criminal decision-making, we were not able to make the distinction between planned and opportunistic criminal behavior. Instead of referring to personal characteristics of offenders, these terms reflect a way of choosing (e.g., Bernasco & Ruiter, 2014; Elffers, 2005). Planned criminal behavior refers to crime journeys that start with the explicit intention to find a suitable target, while opportunistic criminal behavior means that crime is committed more impulsively during ordinary activities based on the opportunities at hand (Bernasco, 2014b; Cromwell et al., 1991). Although it is theoretically meaningful and important to make the distinction between planned versus opportunistic criminal behavior, the environmental criminological research to date (including the current dissertation) has not been able to empirically distinguish between the two. Future research could shed light on the longstanding criminological debate about planned behavior versus opportunistic behavior by investigating several possible scenarios for how the timing and location of a crime are the result of offender decision-making. Note that any individual crime can belong to one of these research scenarios and therefore it is not the case that the scenarios are different models of which only one or a few will be empirically true. A first theoretical scenario could be that offenders choose whether to commit a crime given the time and location (i.e., opportunistic crime). A second scenario could be that offenders choose their crime locations given a certain time (i.e., the time-specific crime location choices in Chapter 3 and Chapter 4). A third scenario could be that offenders choose the timing of their crimes (i.e., offenders' crime time choices in Chapter 5), given the location. A final possibility is that both the location and the timing of a crime are chosen by the offenders (i.e., modelling offenders' crime-time-location choices). To empirically distinguish between these different research scenarios, a next step forward is to ask offenders themselves more in depth about both the spatial and temporal aspects in their criminal decision-making process. For example, future studies could use crime scripts analysis (for an overview, see Dehghanniri & Borrion, 2021) and design semi-structured or more qualitative interviews with active or incarcerated offenders to reconstruct their spatio-temporal choices regarding previous crimes committed in the past (see e.g., Lindegaard, Bernasco & Jacques, 2015).

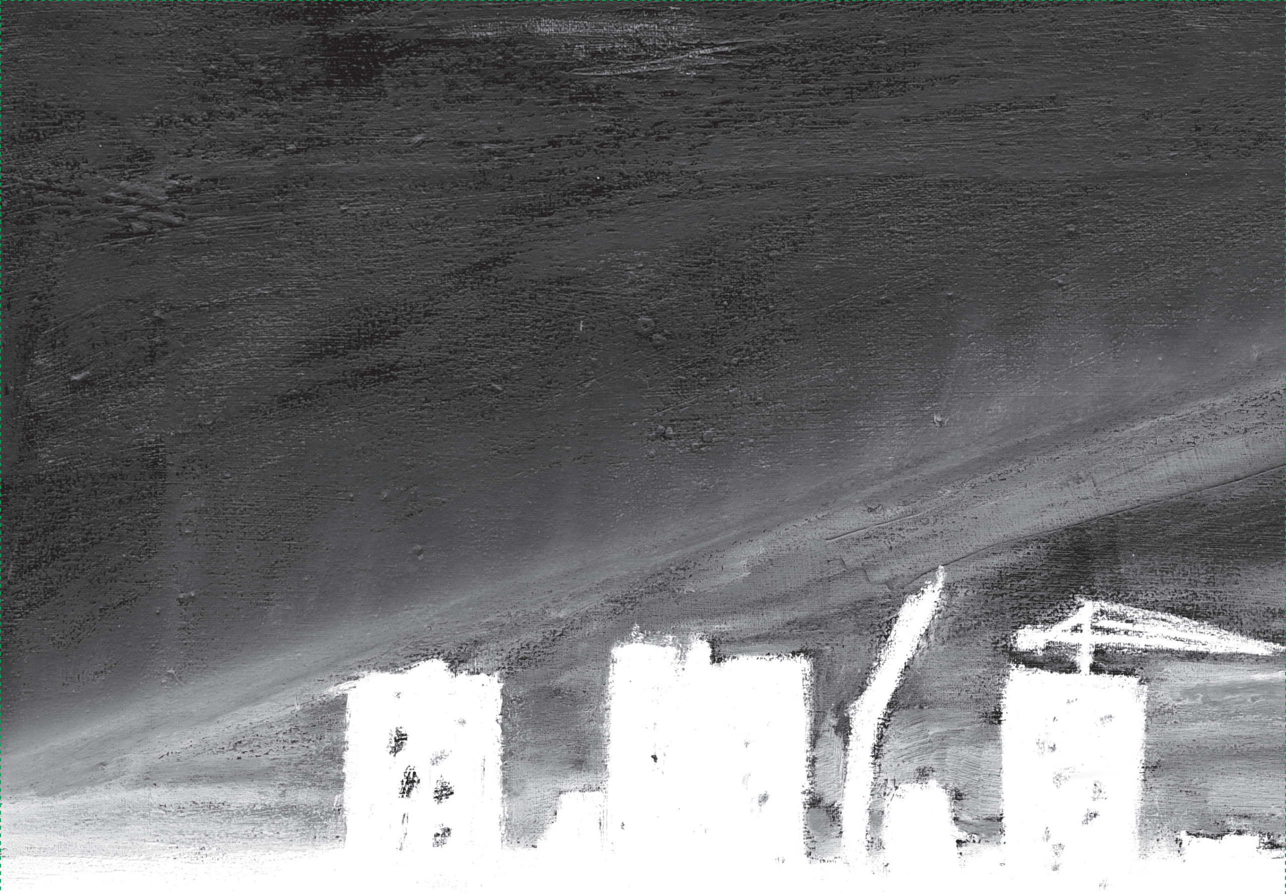
1.5.3 Practical implications

Clearly, the main contribution of this dissertation is scientific as it extends and tests one of the leading theories in environmental criminology. Nevertheless, a better understanding of the spatio-temporal decision-making of offenders could also have practical value. First, it might prove valuable for designing interventions to reduce recidivism among ex-offenders. As most homes are unoccupied during the typical working day on Monday to Friday, this makes them vulnerable for residential burglary. In order to disrupt these opportunities for residential property crime, Cromwell and colleagues (1991) suggested probation and parole conditions that keep offenders busy during working hours. Based on the results of Chapter 2, 4 and 5, we propose a comparable intervention for ex-offenders that are in the stage of reintegrating in society. For example, the probation service might implement reintegration programs that disrupt offenders' previous spatio-temporal crime patterns by actively regulating the times and locations of their current daily routines. When offenders are engaged in employment, education or other non-discretionary activities *during the days and times they had previously committed offenses*, this reduces the opportunity for committing crime at these specific times in the future. We have to note, however, that in Chapter 3 of this dissertation where we focused on explaining the temporal decision-making of a small group of offenders ($N = 30$) by their discretionary and non-discretionary routine activity patterns, our hypotheses were not corroborated. We still believe that our proposed intervention is defensible because of the disconnect between the theoretical expectations and empirical design used in this study (see paragraph 1.5.2).

Second, a better understanding of offenders' spatio-temporal decisions could also help improving predictive policing models (e.g., Bowers et al., 2004; Perry et al., 2013; Rienks, 2015; Mohler et al., 2015). Most predictive policing models rely on the near-repeat phenomenon and solely include spatial and temporal decay functions. The findings of this dissertation show however that (repeat) offenders are also quite consistent in their criminal decision-making with regard to *daily and weekly temporal cycles*: they commit their crimes at similar times of the day and week (Chapter 2), they are more likely to return to previously targeted areas at similar days of the week and times of the day (Chapter 4), and they have a higher chance to commit crime in neighborhoods they have regularly visited before at similar time of the day compared to different times of the day (Chapter 5). More than a decade ago, Johnson et al. (2007b) already developed a predictive approach that takes time of day patterns in repeat victimizations into account. Nevertheless, predictive policing work to date (for an exception, see Rummens, Hardyns & Pauwels, 2017) do not take such cyclical time patterns into account. We believe it is important that future predictive policing models combine the already existing spatio-temporal decay functions with the cyclical time measures within the week and day found in this dissertation. We expect that our proposed addition to the method can relatively easy be incorporated as an extended model, as the data used for predictive policing purposes already contain the relevant information to perform this exercise (i.e., the specific dates and times of the crimes are known).

Finally, the results of this dissertation might also provide opportunities for improving the criminal investigation technique of crime linkage analysis (e.g., Lundrigan & Canter, 2001; Markson et al., 2010; Tonkin, Lemeire, Santtila & Winter, 2019). Repeat offenders are behaviorally consistent in many aspects, including geographical ones (Van Daele & Bernasco, 2012). The idea of crime linkage analysis is to identify a series of crimes as belonging to the same offender based on the consistency of characteristics of the crimes. For example, crimes that occur in spatial proximity or within a short time span are more likely to be committed by the same offender. The findings of this dissertation show that solely focusing on a short time span between crimes might be overly simplistic, as we found support for temporal consistency in individual offending patterns and *cyclical* time patterns in offenders' (repeated) crime location choices. Even if some time has passed, offenders are still more likely to commit crimes around similar hours of day and week (Chapter 2). In addition, they are also more likely to return to previously targeted areas (Chapter 4) or to routinely visited areas (Chapter 5) at similar times of day. Therefore, based on this dissertation we suggest that crime linkage analysis should also include periodically recurring patterns in crime events – by connecting crimes that occur not only shortly after each other in linear time but also that are close to each other in cyclical time. As with predictive policing methods, we expect that these cyclical time measures could relatively easy be added to the analysis without a huge time investment, as the specific dates and times of the crimes are already available in the crime linkage data.

To conclude, extending the existing body of environmental criminology research on the spatial decision-making of offenders, this dissertation shows that studying *temporal* criminal decision-making and its practical implications are also of importance. Future research may combine the different spatio-temporal aspects of offender decision-making that are discussed throughout the four empirical chapters of this dissertation, such as by investigating offenders' crime-time-location choices. This way, we would be able to better address the overarching research questions within environmental criminology of why offenders commit crime both where *and* when they do and why at these locations and times instead of others. In the end, knowing the right place and time for a crime might contribute to a safer future.



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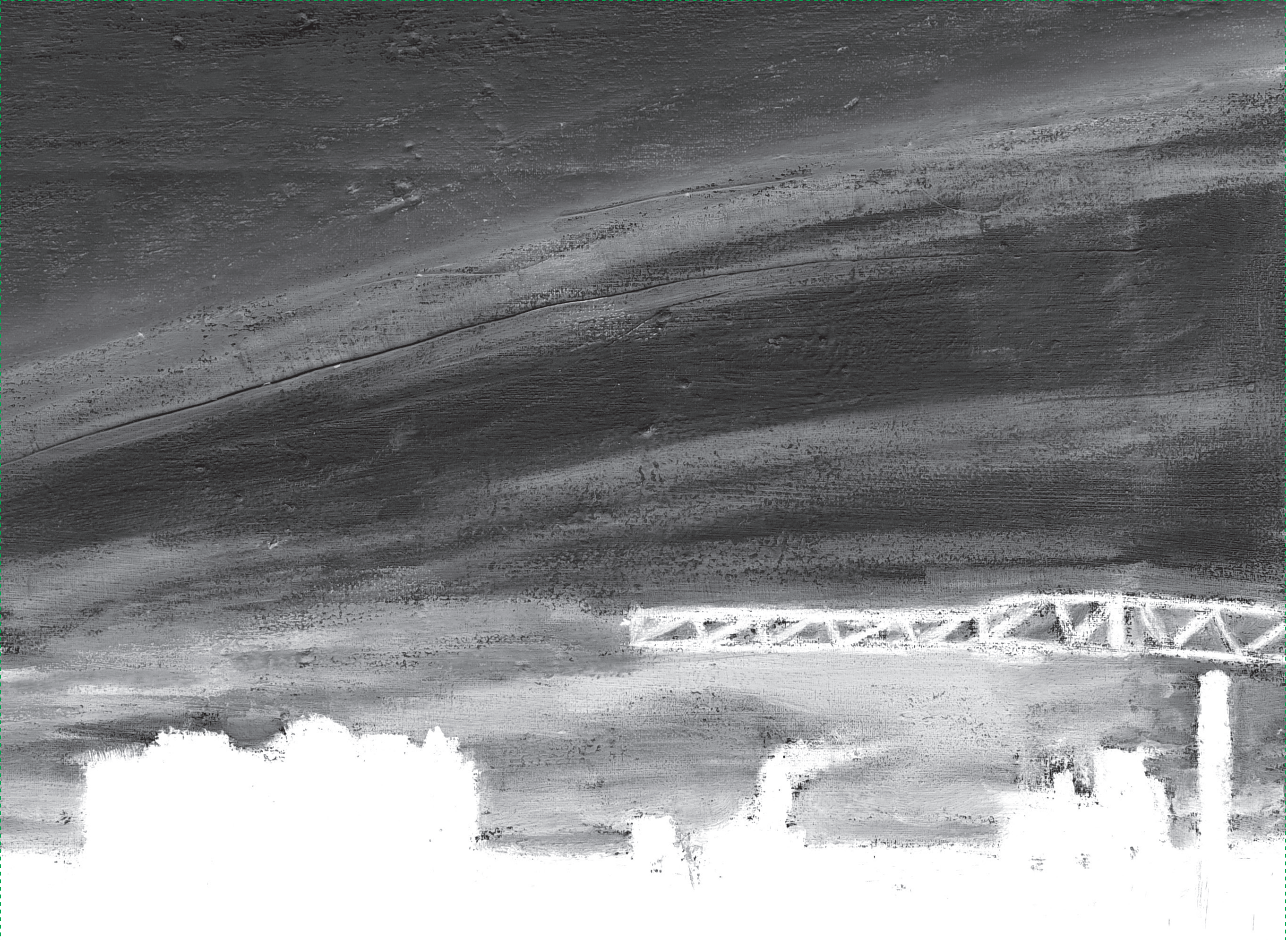


CHAPTER 2

When do offenders commit crime? An analysis of temporal consistency in individual offending patterns

Abstract

Objectives. Building on Hägerstrand's time geography, we expect temporal consistency in individual offending behavior. We hypothesize that repeat offenders commit offenses at similar times of day and week. In addition, we expect stronger temporal consistency for crimes of the same type and for crimes committed within a shorter time span.

Methods. We use police-recorded crime data on 28,274 repeat offenders who committed 152,180 offenses between 1996 and 2009 in the greater The Hague area in the Netherlands. We use a Monte Carlo permutation procedure to compare the overall level of temporal consistency observed in the data to the temporal consistency that is to be expected given the overall temporal distribution of crime.

Results. Repeat offenders show strong temporal consistency: they commit their crimes at more similar hours of day and week than expected. Moreover, the observed temporal consistency patterns are indeed stronger for offenses of the same type of crime and when less time has elapsed between the offenses, especially for offenses committed within a month after the prior offense.

Conclusion. The results are consistent with offenders having recurring rhythms that shape their temporal crime pattern. These findings might prove valuable for improving predictive policing methods and crime linkage analysis as well as interventions to reduce recidivism.[2]

[2] A version of this chapter is published as: Van Sleeuwen, S. E. M., Steenbeek, W. & Ruiter, S. (2020). When do offenders commit crime? An analysis of temporal consistency in individual offending patterns. *Journal of Quantitative Criminology*, 1-27. https://doi.org/10.1007/s10940-020-09470-w.

2.1 Introduction

Why do offenders commit crime at certain times and places instead of others? Crime pattern theory (Brantingham & Brantingham, 2008) posits that offenders should have very consistent *spatial* decision-making behavior. Offenders commit crime in places where their spatial awareness—their knowledge of the environment as acquired while traveling between the places they routinely visit such as their home, work, and leisure activities—overlaps with the spatial distribution of criminal opportunities. Because offenders' awareness spaces and the spatial distribution of attractive targets remain relatively stable over time, offenders are likely to repeatedly commit crime at similar locations: those with the highest utility—perceived benefits minus perceived costs—of which they are aware. A burgeoning body of empirical research has indeed shown that offenders are very consistent in where they commit offenses. Building on crime pattern theory, previous studies have shown that characteristics of offenders' activity spaces, such as their routinely visited places, the distance from their homes to the crime locations, and travel direction from home are all associated with where they commit crime (e.g., Menting et al., 2020; Townsley & Sidebottom, 2010; Van Daele & Bernasco, 2012).

The question whether offenders also exhibit consistent *temporal* patterns in criminal behavior still lacks detailed scrutiny. Human mobility research shows that routine activities clearly differ from one person to the next, but intra-individual patterns show strong recurring daily and weekly rhythms (Gonzalez et al., 2008; Pappalardo et al., 2015; Song et al., 2010). Offenders are obviously also subject to temporal constraints in their daily time budget (Ratcliffe 2006), due to important routines such as work, education and household activities. Therefore, we expect that offenders show temporal consistency in their offending patterns: repeat offenders should commit their crimes at similar times of day and week.

The present study improves research on the geography of crime in two ways. First, we examine the *intra*-offender temporal crime patterns. In contrast, previous research focused on fluctuations in overall crime rates by month of the year (e.g., Andresen & Malleson, 2013), day of the week (e.g., Johnson et al., 2012), time of day (e.g., Haberman & Ratcliffe, 2015) or a combination of these temporal cycles (e.g., Andresen & Malleson, 2015). However, the temporal patterning of crime can be caused by different processes: time-varying criminal opportunities (i.e. attractiveness of targets and presence of potential guardians) and time-varying behavior of offenders. Although previous studies find that crime follows temporally periodic functions (e.g., seasonal, monthly, weekly and daily), such aggregate patterns cannot be used to make inferences about the temporal decision-making of offenders. In other words, it could be possible that the temporal patterns of crime are *entirely* driven by the time-varying attractiveness of targets or shared time-use patterns across offenders and not at all by intra-offender temporally consistent behavior.

Second, we use *large-scale* offending data, which allow for rigorous statistical testing. Several ethnographic studies already showed that residential burglars are quite aware of their own time budget and take predictable time-use patterns of potential victims and guardians into account when committing burglaries (see e.g., Cromwell et al., 1991; Rengert & Wasilchick, 2000; Wright & Decker, 1994). However, their qualitative approach confined them to a small sample of offenders for a specific type of crime, which makes it impossible to generalize the findings from these studies.

2.2 Theoretical framework

2.2.1 Time geography and temporal consistency

Hägerstrand's (1970) time geography identifies several constraints on human mobility: 'capability constraints' (e.g., the necessity to eat and sleep), 'coupling constraints' (e.g., the necessity to work and go to school), and 'authority constraints' (e.g., power relations, economic barriers and general rules and laws in society). For example, the biological need for sleep constrains human movement for long periods of time each day. Due to specific office hours, most jobs represent a restricted activity for a substantial part of the day and the (work) week for employed people. Because of this compulsory character and the large amount of time these routine activities require, they strongly affect the degree of flexibility people have in their daily and weekly time budget. In turn, these constraints on human activities in space and time are informative for one's potential spatial movement. Miller (2005) provides analytical formulations of the basic time geography concepts, such as the space-time prism—the ability to reach (be coincident with) locations in space and time given the location and duration of fixed activities—which can be calculated using one's time budget, the travel time between locations, and the duration of the intended activity. This concept was introduced in criminology by Ratcliffe (2006), who argued that the spatial range of a foraging offender is affected by his available time as he is bound to other (spatially and temporally) fixed activities. Thus, Ratcliffe argued that temporal constraints strongly affect spatio-temporal patterns of opportunistic crimes.

While Ratcliffe and indeed Hägerstrand argued that temporal constraints are important for understanding spatial patterns in human behavior, we are not aware of any criminological literature that directly investigated to what extent temporal constraints actually affect *temporal* patterns of crime. As most crimes often only take a short time to complete ((Bernasco, Ruiter, Bruinsma, Pauwels & Weerman, 2013; Ruiter & Bernasco, 2018) and only few offenders commit crime so regularly that it takes a considerably share of their time budget, most offenders will have activity patterns that closely resemble those of non-offenders. They sleep at regular times, might go to work during business hours, do household chores, and spend time in leisure activities. Their activity patterns might also differ considerably, with some offenders spending most of their evenings and weekends on leisure activities away from home while others might stay at home (see Rengert & Wasilchick, 2000). Some attend school regularly or have a 9-to-5 job and thus will usually be travelling around the edges of these office hours from Monday to Friday. Others may have much more free time during the day. Although large inter-individual differences exist, mobility research shows that *intra*-individual activity patterns are actually highly regular (Barabasi, 2005; Gonzalez et al., 2008; Pappalardo et al., 2015; Song et al., 2010). That is, the same person generally performs the same activities at similar times. We assume the same applies to offenders and thus that their non-criminal daily routine activities delineate the timing of their criminal activities. This leads to the expectation of temporal consistency in individual offending behavior, which we define here as repeatedly committing offenses at similar times of day and week. Our first and general *temporal consistency hypothesis* thus reads:

> ***Hypothesis 1***: Offenses committed by the same offender are more temporally consistent than is to be expected based on the overall temporal distribution of crime.

2.2.2 Type of crime

In order for a crime to occur, a motivated offender and a suitable target have to converge in space and time in the absence of a capable guardian (Cohen & Felson, 1979). Consequently, temporal patterns in crime depend not only on the temporal constraints of offenders, but also on those of potential victims and guardians. Because they too have temporally consistent time-use patterns (e.g., Cromwell et al., 1991; Rengert & Wasilchick, 2000; Wright & Decker, 1994), different types of crime will have different time-varying opportunity structures. For example, most residential burglars try to minimize the risk of apprehension by targeting houses during the day when nobody is home (e.g., Rengert & Wasilchick, 2000; Wright & Decker, 1994) and levels of guardianship are low (Coupe & Blake, 2006). Thus, own time permitting, an offender is most likely to commit a residential burglary during office hours. However, would the offender commit pickpocketing instead, it would probably happen at places where large numbers of people gather such as shopping malls, and thus most likely during the time window when the opening hours of the mall overlap with a period in which the offender faces no time constraints. This leads to our second hypothesis:

> ***Hypothesis 2***: The temporal consistency as hypothesized in Hypothesis 1 is stronger for offenses of the same crime type than for offenses of a different crime type.

2.2.3 Recency of offenses

Although time-use patterns of offenders should be relatively stable, as time passes everybody's activities change. First, big life events can affect offenders' routine activities. For example, the birth of a child or a job change cause changes in the constraints on one's time budget. Second, opportunity structures change with the passing of time, such as the opening or closing of bars or shops, which could influence the number of people at certain places at certain days and times. Recent mobility research indeed shows that human behavior is most regular within a short time span (e.g., Gonzalez et al., 2008). In addition, the study of Lammers et al. (2015) showed that offenders are more likely to return to previously targeted areas the more recently they committed the previous offense. Therefore, we expect the strongest temporal consistency when offenses are committed shortly after one another and less so when the offenses are a long time apart. This leads to our final hypothesis:

> ***Hypothesis 3***: The temporal consistency as hypothesized in Hypothesis 1 is stronger the less time has passed between the offenses.

2.3 Data and methods

2.3.1 Data source

To study temporal consistency in offending and test our hypotheses, we use police data from the greater The Hague area in the Netherlands. Information on all registered offenders between 1999 and 2009 was obtained from the Dutch Suspect Identification System (in Dutch "Herkenningsdienstsysteem [HKS]") used by The Hague Police Service, including information on the specific date, time and type of their offenses. In order to keep the length of all offense histories equal, we study temporal consistency in repeat offending within a maximum of 3 years between the offenses. If an offender has a criminal history in which some crime pairs are more than 3 years apart while other pairs are within that range, only those crime pairs that meet our criterion will be included. Our sample consists of offenders who committed at least two crimes at most 3 years apart in the study area between 1996 and 2009. It is important to note that all offenders are recorded as 'suspects' in this police database. Although these cases were submitted to the public prosecutor's office, the police suspect database does not contain information on the final court decisions for individual suspects. However, the cases of over 90% of the suspects in the HKS system are at a later stage either settled by the public prosecutor or lead to a conviction in criminal court (Besjes & Van Gaalen, 2008; Blom et al., 2005).

2.3.2 Crime times and crime types

Each crime record in the Dutch police data has two time variables, one related to the start date/time and one related to the end date/time. These variables scored similar in most cases, although there were some exceptions that range from small differences within the hour to larger differences within the week. For some types of crime, such as residential burglary, victims are generally not present during the offense, and they can therefore not accurately report on the exact timing of the offense. Other offenses, such as long-term abuse, cannot be assigned a single point in time, but rather stretch over a longer time period (Ratcliffe, 2002; Van Sleeuwen, Ruiter & Menting, 2018; Chapter 4). In this study, only offenses with a maximum of 24-hour difference in start and end time are included, as differences exceeding 24 hours are not informative for our analyses when examining a daily temporal rhythm. Descriptive analysis of the recorded crime times showed systematic patterns within each hour: for example, crimes are most often recorded to happen at the start of each hour and half past, or quarter past and quarter to the hour. As it is unlikely that these timings reflect actual temporal offending behavior but rather that the police has rounded the times to convenient values, we rounded all times to the nearest hour and use these hours in subsequent analyses.

The analyses presented in this paper use the end dates and times of the offenses, as they are expected to yield the most reliable information. Because a crime event can only be reported after its commission, we expect people to generally report end times more accurately than start times. For example, suppose someone gets home to discover the home was burglarized. We assume that they will then watch the clock and remember the time they got home, while they might have less accurate knowledge about the specific time they left the home earlier that day. To check whether the findings are sensitive to our choice of using crimes' end dates and times, we repeated all analyses using the start dates and times instead of the end records, as well as the midpoint between the start and end times.

We classified crime type according to the standard 8-type classification of Statistics Netherlands (2014): violent crimes, property crimes, vandalism, traffic crimes, environmental crimes, drug crimes, weapon crimes, and other types of crime. Because we expect the timing of traffic offenses to primarily reflect law enforcement's temporal choices rather than the offenders', we do not include traffic offenses in our analyses. To measure the recency of offenses, i.e. the number of days between the offenses, we distinguished three different categories: within one month (0-30 days), between a month and half a year (31-183 days), and between half a year and three years (184-1096 days).

Table 2.1 gives an overview of the frequencies of offenses by crime type (N = 152,180 offenses) and the total number of crimes per offender (N = 28,274 repeat offenders). Additionally, the temporal distributions over the week across the different crime types are shown in Figure 2.1, while these are broken down by crime type in Figure 2.2.

Table 2.1 Frequency of offenses by type of crime and total number of crimes per offender (N = 152,180 offenses committed by 28,274 offenders).

Variable	Variable labels	Count	Percentage (%)
Type of crime		*152,180*	*100.00*
	Violence	35,953	23.63
	Property	78,181	51.37
	Vandalism	22,561	14.83
	Environmental	1,620	1.06
	Drugs	5,254	3.45
	Weapons	3,299	2.17
	Other	5,312	3.49
Total number of offenses		*28,274*	*100.00*
(per offender)	2 offenses	11,830	41.84
	3 offenses	5,174	18.30
	4 offenses	2,847	10.07
	5 offenses	1,824	6.45
	6 offenses	1,240	4.39
	7 offenses	901	3.19
	8 offenses	679	2.40
	>8 offenses	3,779	13.37

Note: percentages do not total 100 due to rounding.

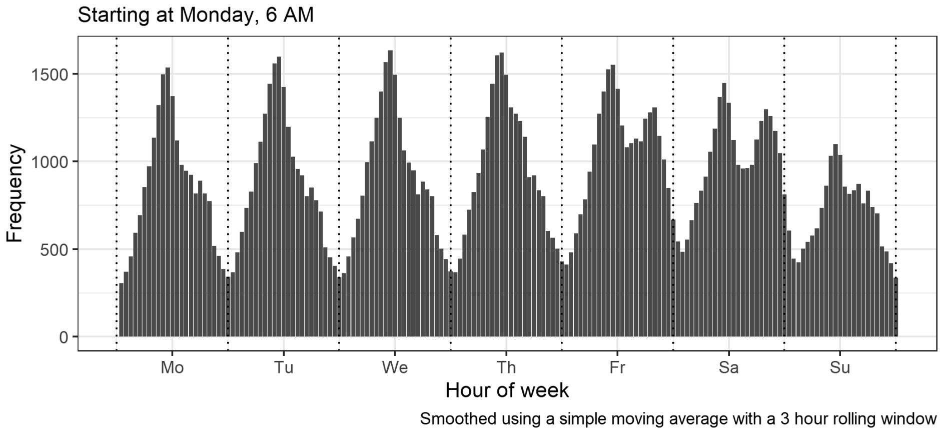


Figure 2.1 Crime frequency during the week (N = 152,180 offenses committed by 28,274 offenders).

Table 2.1 shows that more than 75% of the repeat offenders committed only two to five offenses, and almost 90% of all offenses were categorized as violent crime, property crime or vandalism. Figure 2.1 shows that the timing of offenses is not uniformly distributed over the day and week. We observe, for example, that most crimes are committed during the afternoon and weekend nights, while few crimes are committed in the early morning. We also observe clear differences between types of crime in Figure 2.2. For example, property crimes occur more often during the day for every day of the week, while vandalism peaks in the evening on Friday and Saturday night.

2.3.3 Temporal consistency

We define temporal consistency as a clustering in the daily and weekly patterns of crimes committed by the same offender. We analyzed temporal consistency with regard to two temporal scales: hour of day (24 hours in total) and hour of week (168 hours in total). First of all, we expect crimes of repeat offenders to exhibit a *daily temporal rhythm*: if an offender commits a first crime at 1 p.m., we expect him to commit another crime in the near future around that same time of day (regardless of the exact day of the week). We also hypothesize that repeat offenders exhibit *weekly temporal rhythms*: if an offender commits a crime on a Friday at 11 p.m., we expect that it is more likely that a second crime by the same offender will also be committed around that time of week.

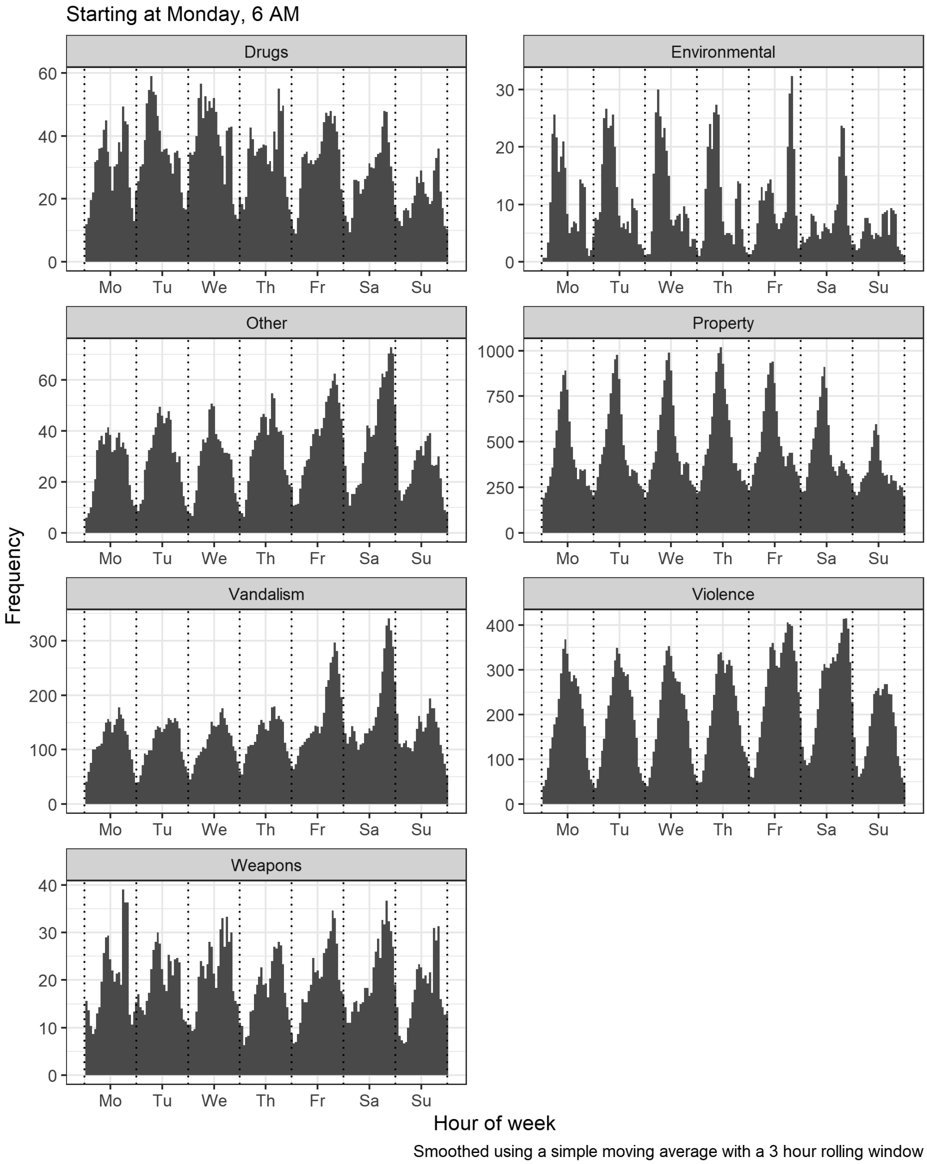


Figure 2.2 Crime frequency during the week, by crime type ($N = 152{,}180$ offenses committed by 28,274 offenders).

Specifically, we take the following steps to calculate the degree of temporal consistency:

(a) *Generate crime pairs:* all combinations of an offender's crime events that are at most 3 years apart. For example, an offender with 3 crimes can have a maximum of 3 crime pairs (1-2, 1-3, 2-3), while an offender with 5 crimes can have up to 10 crime pairs (1-2, 1-3, 1-4, 1-5, 2-3, 2-4, 2-5, 3-4, 3-5, 4-5).[3]

(b) *Calculate the circular temporal distance between the two crimes of each pair.* For each crime, we first calculate the number of hours since the start of the day (the chosen "start" is arbitrary and does not affect subsequent analyses; we used 0:00 a.m.) and the number of hours since the start of the week (we used Monday 0:00 a.m. as the arbitrary start of the week). Then, the circular distances between the daily and weekly hours are calculated.[4] For example, an offense-pair of an offender who committed his first offense at 11 p.m. on a Saturday and the second offense at 4 a.m. on a Monday (or the other way around), has a 5-hour distance on the 24-hour (daily) clock and a 29-hour distance on the 168-hour (weekly) clock.

Then, across all offenders:

(c) *Construct the proportion table of temporal distances.* We calculated the proportion of crime pairs that is committed with a specific temporal distance by dividing the number of crime pairs that is committed with a certain circular temporal distance by the total number of pairs. The first cell of the table thus represents the proportion of all crime pairs that are committed on the exact same hour of day (or hour of week), the second cell gives the proportion of crime pairs committed one hour apart, and so on.[5]

(d) *Convert the proportion table of step c into cumulative proportions*, by summing the proportions of the consecutive temporal distance categories.

(e) *Take the sum of the cumulative proportions of step d.* The sum of cumulative proportions has a theoretical range of 1-13 for the daily cycle: if all offenders commit two crimes 12 hours apart, 100% of all crime pairs are found in the final category ("12-hour distance") and the sum of the cumulative proportions across all

[3] The formula to calculate the number of combinations is $n * (n - 1)/2$, where n equals the total number of crimes per offender.

[4] Calculating the circular time distances was done by taking the smallest absolute difference between the two times of each crime pair. These times can thus be seen as two points on a distribution that is "wrapped" around the circumference of a clock.

[5] For hour of day, there are 13 circular temporal distance categories: 0-hour, 1-hour, 2-hour, …, 12-hour distance. For hour of week, there are 85 circular temporal distance categories: 0-hour, 1-hour, 2-hour, …, 84-hour distance.

temporal distances is $0 + 0 + 0 + \cdots + 1 = 1$. If all offenders commit all crimes at exactly the same hour of day, 100% of crime pairs are found in the first category ("0-hour distance") and the sum of the cumulative proportions is $1 + 1 + 1 + \cdots + 1 = 13$. Similarly, the sum of cumulative proportions has a theoretical range of 1-85 for the weekly cycle.

(f) *Create a standardized scale of temporal consistency*. The sum scores of step *e* have several disadvantages. First, the values are not easy to interpret substantively. Second, the range of the sum scores are sensitive to the choice of temporal distance unit (here we used hours). Third, the values are not directly comparable between two different temporal scales (i.e. hour of day versus hour of week). Therefore, we rescale the outcome of step *e* to a range of $\{-1, 1\}$.[6] Hereafter, we refer to this measure as the "observed temporal consistency", or TC_{obs}. Positive values of TC_{obs} indicate temporal consistency in the data: summarizing across all offenders, we see evidence that they repeatedly commit offenses at similar hours of day and week. A value of zero—the original midpoint of the scale in step *e*—indicates that, summarized across all offenders, the timings of crimes exhibit no discernible consistency (i.e. random temporal behavior).[7] Negative values of TC_{obs} indicate that offenses are committed at dissimilar hours of day and week. Note that because of the standardization, the outcome of step *f* directly indicates the degree of temporal consistency in the data and is comparable regardless of time scale (day versus week).

2.3.4 A Test of intra-offender temporal consistency

While the result of the previous steps shows the degree of temporal offending consistency in the observed data, we cannot yet be certain that any observed consistency is due to *intra*-offender consistency in offending times: the temporal patterning of crime can also be the result of time-varying opportunities for crime (i.e. the combined influence of attractive targets and

[6] The formula to rescale a value of X to a $\{-1,1\}$ range is $(X - 1)/12 * 2 - 1$ for hour of day and $(X - 1)/84 * 2 - 1$ for hour of week.

[7] We can easily derive the theoretically expected cumulative proportions under complete temporal randomness. When there would be an equal chance of crime happening on each hour of day or week, the expected proportions per distance category are {1/24, 1/12, 1/12, …, 1/12, 1/12, 1/24} for the daily cycle, and {1/168, 1/84, 1/84, …., 1/84, 1/84, 1/168} for the weekly cycle. The sums of their cumulative proportions are 7 and 43, respectively, i.e. the exact midpoints of the 1-13 and 1-85 scales, which both receive a value of 0 on the standardized scale.

guardians), or because all offenders have similar time-use patterns. Therefore, a certain degree of consistency observed in our data could also be due to other sources of temporal variation, which would make *all offenders* more likely to commit crimes at certain times of the day or week. In the present study, we want to assess to what extent offenders' offending times are temporally consistent *over and above* any such daily and hourly rhythms of potential targets and guardians, and shared characteristics of the offender population. Because the observed data are the result of a mixture of these sources of variation, we need to perform a test that is able to isolate intra-offender temporal behavior. In order to do so, we use a Monte Carlo permutation test.

The basic idea of our Monte Carlo permutation test is to compare the observed temporal consistency with a simulated reference distribution of temporal consistency values from which the intra-offender temporal variation is removed. We simulate the distribution because there is no other way of knowing the remaining temporal variation, and we use a sample of permutations of the data because a full permutation is virtually impossible to calculate even with moderately sized data (Johnson et al., 2007a). We randomly permute the original dataset many times to generate a distribution of temporal consistencies derived under the null hypothesis. We subsequently compare the observed temporal consistency with the distribution of permutated temporal consistencies to assess the likelihood of observing the former. Our hypotheses imply that individual offenders' crime events should show more temporal consistency than what is to be expected if they were the result of daily and weekly rhythms of criminal opportunities and shared time-use patterns across offenders. Specifically, we take the following steps to perform the Monte Carlo permutation test:

(1) *Using the observed crime data, randomly shuffle the offender IDs* using a pseudorandom number generator while we keep the observed date/timestamps and crime types unchanged, so that the crime events still have the original temporal distributions per crime type (as shown in Figure 2.2). It is important to keep the connection between the temporal information and crime types fixed for each offense, because this resembles the temporal variation caused by other sources of variation in our data.

(2) *Run the permutated data through steps a through f* as described in paragraph 2.3.3.[8]

[8] As only crime pairs that are at most 3 years apart are included in the analysis (see paragraph 2.3.1), the number of valid crime pairs generated in step *a* changes with every permutation. More specifically, this number is probably lower than the number of crime pairs for the observed data, since it is much more likely that two offenses are more than 3 years apart if they are random draws from all crimes.

(3) *Repeat steps 1 and 2 9,999 times*. This leads to 9,999 values of temporal consistency that is to be expected given the overall temporal distribution of crime events, one for each of the 9,999 permutated datasets. We will refer to the mean of the 9,999 temporal consistency values of the permutated datasets as TC_{perm}.

(4) *Calculate a pseudo p-value* using the formula $p = (n - rank + 1)/(n + 1)$, where n is the number of permutations, and *rank* is the position of the observed value in a rank-ordered array (Johnson et al., 2007a; North, Curtis & Sham, 2002). Under the null hypothesis, it is very unlikely that many of these 9,999 temporal consistency values are larger than the observed temporal consistency.

Note that an estimate of effect size of the *intra*-offender temporal consistency can be calculated by taking the difference between the observed temporal consistency and the 9,999 temporal consistency values of the permutated datasets. The mean of these values is the best point estimate of the intra-offender effect, hereafter TC_{intra} (we discuss this in more detail in the Results section, see Figure 2.4).[9] In addition, because the *TC* values are standardized, they are also comparable across temporal scales (here, the daily versus weekly cycle).

2.3.5 Sensitivity analysis

In the next section, the results are shown for all offenders. However, Table 2.1 shows that there are clear differences in the total number of offenses per offender. Most offenders were suspected of committing only a few crimes, and only a few were much more prolific. Because temporal consistency of a few prolific offenders might drive the outcomes, we also performed our Monte Carlo permutation tests separately for four different groups of offenders: those that committed 2, 3, 4 or 5 offenses, which altogether account for more than 75% of the offenders in our data (see Appendices A–C for the separate graphs per number of offenses for the three different hypothesis tests). We also tested whether the results were sensitive to our choice of using the end dates and times of the offenses (see paragraph 2.3.2). In additional analyses (not shown here), we observed substantively similar findings when using the start dates and times instead of the end records, as well as when using the midpoint between the start and end times.

[9] Equivalently, we can take the difference between TC_{obs} and TC_{perm} (recall that TC_{perm} is the mean of the consistency values across the 9,999 permutated datasets).

2.4 Results

This section shows the results for the hour of day and hour of week consistency analyses. We start our presentation of the results with Figure 2.3, which shows the proportions of crime pairs that are committed in recurring hourly rhythms for the observed data and the total range of proportions across the 9,999 permutated datasets, i.e. these results refer to step *c*. We observe that almost 7% of the crime pairs occur within the same hour of day and almost 20% of the crime pairs are either 0 or 1 hour apart (see Figure 2.3, left). Half of the crime pairs consist of crimes committed with a distance of 0 to 4 hours. In line with our hypotheses, we see a higher proportion of crime pairs at shorter temporal distances.

Because the hour of week distances have a range of 0-84 (see Figure 2.3, right), the proportions for each distance are naturally smaller than those for hour of day, reflected in different scales on the y-axis. The hour of week proportions show that there is much intra-week variability. Note, however, that the four peaks across the 84-hour of the cyclical week steadily diminish in size. These results indicate that offenders are most likely to commit multiple crimes on a similar hour of day, but also that offenders are slightly more likely to commit multiple crimes on the same hour of week (otherwise the four peaks would have the same height).

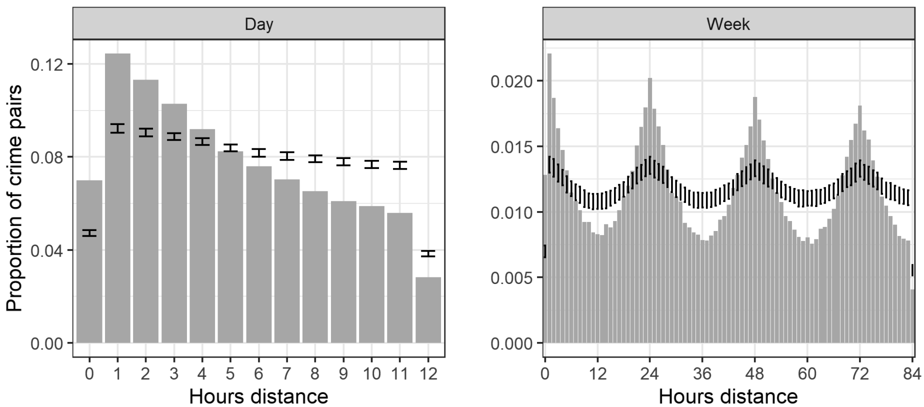


Figure 2.3 Proportions of crime pairs by distance in hours of day and hours of week for the observed data (bars), and the total range across the 9,999 permutated datasets (N = 28,274 offenders).

For each hour distance, we also display the total range of proportions of crime pairs across the 9,999 permutated datasets. For the daily cycle, it is clear that the permutated datasets also exhibit some temporal consistency, i.e. higher proportions of crime pairs are found at shorter temporal distances. For the weekly cycle, the temporal consistency seems to show no discernible pattern other than the intra-week variation, but is difficult to be certain from this figure. We next turn to the results of our actual hypotheses tests, which formally examine how unlikely the observed temporal consistency—i.e. the standardized sum score of the cumulative proportions of crime pairs across the temporal distances—is given a distribution of temporal consistency values based on the 9,999 permutated datasets.

2.4.1 Temporal consistency by hour of day and hour of week

We first display visually the outcome of the first hypothesis test regarding temporal consistency in individual offending patterns, i.e. step 4 of our procedure. Figure 2.4 (left) shows the hour of day consistency observed in the original data (black dashed line), the distribution of temporal consistency values across the 9,999 permutated datasets (in grey), and a dotted line at zero for reference indicating random temporal behavior.[10]

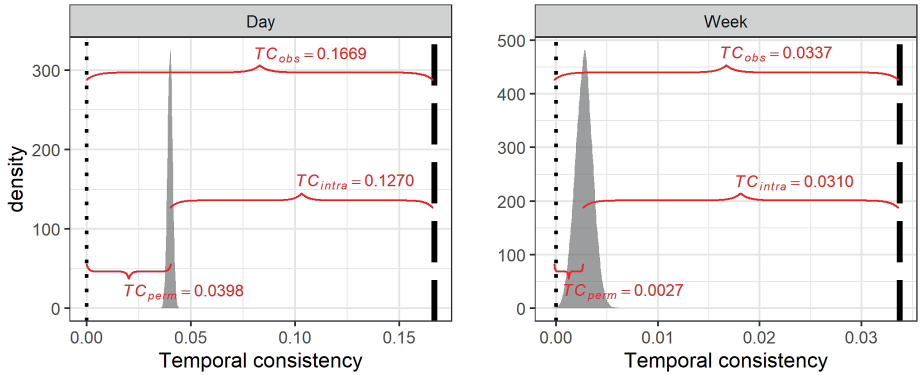


Figure 2.4 Visualization of the statistical significance test outcome for Hypothesis 1. The figure shows the hour of day consistency (left) and hour of week consistency (right), and presents key concepts used in the paper (N = 28,274 offenders). The dotted line at zero indicates random temporal behavior; TC_{obs} = observed temporal consistency in the data (black dashed line), calculated as the standardized sum score of the cumulative proportions of crime pairs across the temporal distances; TC_{perm} = the mean of the temporal consistency values observed across the 9,999 permutated datasets (grey distribution); TC_{intra} = the intra-offender temporal consistency (i.e. $TC_{obs} - TC_{perm}$).

On a scale of 0 (random temporal behavior) to 1 (all offenders commit their crimes at exactly the same hour of day), the observed temporal consistency TC_{obs} equals 0.1669. The Monte Carlo

[10] Note: in order to clearly depict the differences between the observed temporal consistency and the 9,999 temporal consistency values of the permutated datasets, we use different axes for the hour of day and hour of week analyses.

procedure allows us to separate this value into a unique intra-offender temporal consistency part and other sources of variation. The possible temporal consistency values that is to be expected given the overall temporal distribution of crime are displayed by the grey distribution, which has a mean of 0.0398 (TC_{perm}). The mean estimate of the *intra*-offender temporal consistency, over and above the expectation given the temporal patterns of target attractiveness and similar temporal choices across offenders, is the difference between the observed temporal consistency and the mean of the 9,999 temporal consistency values: $TC_{intra} = TC_{obs} - TC_{perm} = 0.1270$. Put differently, of the total observed temporal consistency, about (0.1270/0.1669 =) 76% is attributable to intra-offender temporal consistency. As the dashed line doesn't overlap at all with the grey distribution, it will come as no surprise that the observed temporal consistency is statistically significantly higher than the temporal consistency that is expected given the temporal distribution of crime ($p = 0.0001$).

For hour of week, $TC_{obs} = 0.0337$ (see Figure 2.4, right), and TC_{intra}—i.e. the difference between the observed temporal consistency and the mean of the 9,999 consistency values of the permutated datasets—equals 0.031. While the effect is statistically significant ($p = 0.0001$), $TC_{intra(week)}$ is notably smaller than $TC_{intra(day)}$. These temporal consistency effects clearly differ in size, and a separate test indeed shows a statistically significant difference between these effect sizes, $p = 0.0001$.[11] Of the very small weekly temporal consistency that is observed, about 92% is attributable to *intra*-offender behavior.

While Figure 2.4 displays the outcome of the statistical significance test for the first hypothesis, for subsequent analyses it is unnecessary to plot this figure every time. We do think it will be helpful to present the *cumulative proportions* of crime pairs across the hour of day and week distances, i.e. the outcome of step *d*, together with the key values with which to test our hypotheses and get an estimate of effect size (TC_{obs}, TC_{perm}, TC_{intra}, and the *p*-value). Figure 2.5 presents these observed cumulative proportions for the daily and weekly cycle in dashed red, while the cumulative proportions for 200 permutated datasets are presented as solid lines (for readability, we only draw 200 of the 9,999 outcomes, and we draw continuous lines rather than steps or bars). The key outcomes after taking steps *e* through *f* and steps 1 through 4 are shown bottom-right. For each of our remaining hypotheses and sensitivity analyses, we will plot the cumulative proportions of crime pairs by hour distance and provide the key values of our tests embedded in the figure.

[11] I.e., whether the dashed line for hour of day consistency is farther away than the dashed line for hour of week consistency from their respective distributions of expected temporal consistency values. Note: we did not hypothesize a priori about a difference in effect size of hour of day versus hour of week.

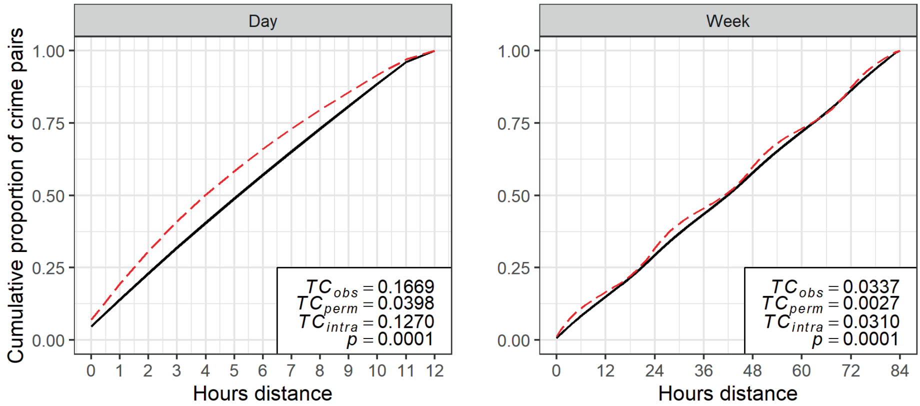


Figure 2.5 Cumulative proportions of crime pairs by distance in hours of day and hours of week for the observed data (dashed red), and 200 of the 9,999 permutated datasets (solid lines) (N = 28,274 offenders). Key values are displayed in the bottom-right corner. The p-values indicate whether TC_{obs} is significantly larger than expected in its respective plot.

Sensitivity analyses of the four different offender groups that committed 2, 3, 4 or 5 offenses respectively show comparable results for the test of Hypothesis 1 as discussed above, but with considerably larger TC_{obs} and TCi_{ntra} values, especially for the hour of week results (see Appendices A1 and A2). With regard to our first hypothesis, we conclude that offenses committed by the same offender are more temporally consistent than is to be expected based on the overall temporal distribution of crime.

2.4.2 Temporal consistency by type of crime

We now turn to Hypothesis 2, which refers to an effect *difference*: we expect temporal consistency to be stronger for crime pairs of the same type of crime than for pairs of different crime types. To test this hypothesis, the basic significance test needs to be adjusted slightly. We need to compare the observed temporal consistency and the 9,999 temporal consistency values of the permutated datasets between (1) pairs of crimes of the same type and between (2) pairs of crimes of different types. It is important that each offender in the permutated data still commits the same types of crimes with the same frequency as in the observed data, so that the number of same crime-type pairs and the number of different crime-type pairs remains the same. Therefore, we need to carry out the permutations independently within each crime type. That is, we first permute the offender IDs for violent crimes, then for property crimes, and so on. After carrying out these adjusted permutations for the seven different types of crime, we calculated the standardized sum of the observed cumulative proportions and the standardized sum of the cumulative proportions in each of the 9,999 permutated datasets separately for same crime-type pairs and for different crime-type pairs. The test of the second hypothesis is then a comparison of $TC_{intra(same\ type)}$ and $TC_{intra(different\ type)}$, or more formally, how often $\sum_{i=1}^{n}\left(TC_{obs(sametype)} - TC_{obs(differenttype)}\right) > \left(TC_{i,\mathrm{sim}(sametype)} - TC_{i,\mathrm{sim}(differenttype)}\right)$for $i=1,\ldots,9999$ permutated datasets.

The cumulative proportions for the same type and different type crime pairs are presented in Figure 2.6 (top: hour of day; bottom: hour of week). The *p*-values in the figure refer to the deviation of the standardized sum score of the dashed red line from the distribution of standardized sum scores of solid lines. The second hypothesis refers to the difference between the left and right parts of the figure, or put informally; is TC_{intra} for same crime-type pairs significantly higher than TC_{intra} for different crime-type pairs?

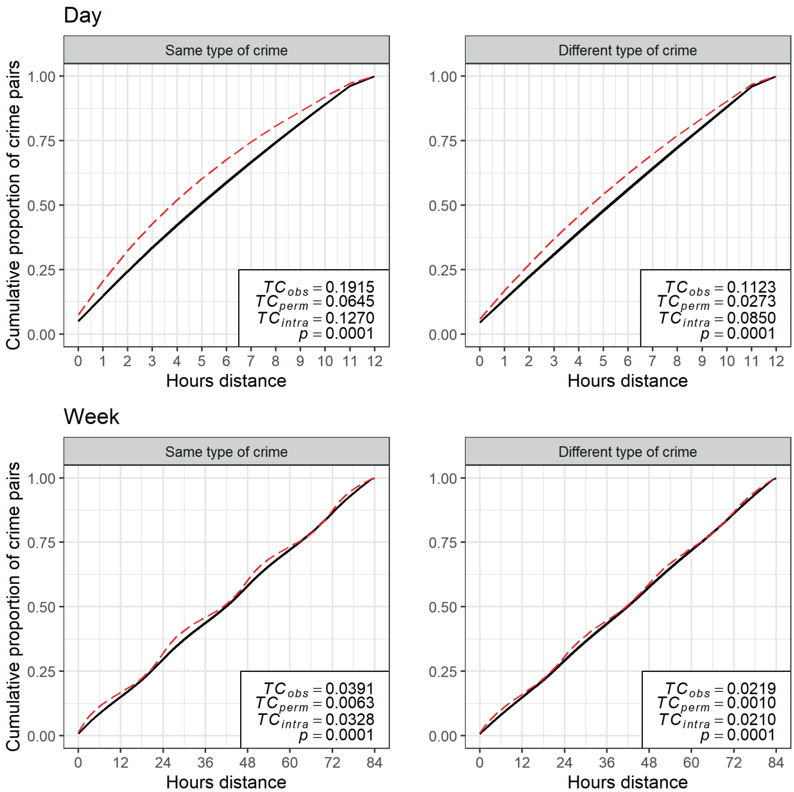


Figure 2.6 Cumulative proportions of crime pairs for hour of day (top) and hour of week (bottom), for crime pairs of the same crime type (left) and crime pairs of a different crime type (right). The hypothesis tests the *difference* between left and right figures (N = 28,274 offenders).

For both hour of day (Figure 2.6, top) and hour of week (Figure 2.6, bottom), we can indeed reject the null hypothesis of no effect difference (p = 0.0001). Note, however, that the differences are very small: (0.1270 − 0.0850 =) 0.042 for hour of day and (0.0328 − 0.0210 =) 0.012 for hour of week, which means that substantively we hardly detect any difference in *intra*-offender temporal consistency when considering crime pairs of the same crime type or of dissimilar types. For the offenders that commit either 2, 3, 4 or 5 crimes, and together comprise more than 75% of all offenders in our data (see Appendices B1 and B2), we also reject the null hypothesis of no effect difference (for all groups, p = 0.0001). Importantly, the effect size differences are also *substantively meaningful* for these offender groups: the differences between $TC_{intra(same\ type)}$ and $TC_{intra(different\ type)}$ now approach a 0.1 on a scale from 0 (temporal consistency that is consistent with random choices) to 1 (perfect temporal consistency). In line with our second hypothesis, we conclude that temporal consistency in offending is stronger for offenses of the same type of crime than for offenses of a different type of crime, especially when looking at offenders that commit either 2, 3, 4 or 5 crimes.

2.4.3 Temporal consistency by recency of offenses

Hypothesis 3 also implies an effect difference: we expect that intra-offender temporal consistency is stronger for crimes that are committed within a shorter time span. Two tests are performed: a comparison of 0-30 days (one month) versus 31-183 days (one month to half a year), and a comparison of 31-183 versus 184-1096 days (half a year to three years). For hour of day, the cumulative proportions of crime pairs for the three different recency categories are presented in Figure 2.7. Statistical tests on the difference of these effects show that temporal consistency with regard to hour of day is indeed stronger within 0-30 days between crimes than within a period of a month to half a year (p = 0.0001). The effect is also substantively meaningful, with mean expectation of (0.1827 − 0.1103 =) 0.072. We do not find evidence for more temporal consistency when comparing 31-183 to 184-1096 days between crime events (p = 0.9998). The sensitivity analyses show that our overall finding is corroborated for offenders that commit either 2, 3, 4 or 5 crimes, and with much larger effect sizes (see Appendix C1). Again, these sensitivity tests highlight the importance of separating prolific offenders from the majority of the offenders.

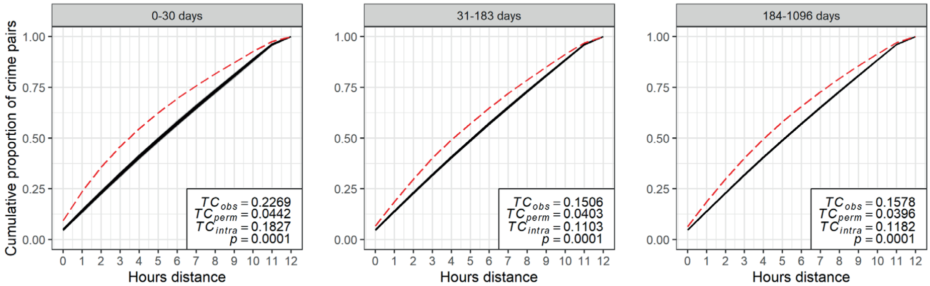


Figure 2.7 Cumulative proportions of crime pairs for hour of day within 0-30 days (left), 31-183 days (middle) and 184-1096 days (right). The hypothesis tests the *difference* between left and middle, and middle and right figures (N = 28,274 offenders).

As displayed in Figure 2.8, temporal consistency with regard to hour of week is also stronger for crime pairs that are committed within 0-30 days compared to 30-183 days ($p = 0.0001$). The mean size of the difference is (0.1057 − 0.0114) = 0.094, which is higher than that found for hour of day. We cannot reject the null hypothesis when comparing crime pairs within 30-183 days with 184-1096 days recency ($p = 0.6041$). Sensitivity analysis of separate groups of offenders show comparable results: the null hypothesis is always rejected for the former, but never for the latter comparison (see Appendix C2). Note that the TC_{intra} values for hour of week are *much* higher for these less prolific offenders: crime pairs within the month show striking weekly consistency, with an overabundance of crime pairs with relatively similar hours of week, in contrast to our main result of Hypothesis 1. Overall, we can conclude that the temporal consistency pattern we observed is stronger for shorter time spans between the offenses, but only for offenses that are committed within 1 month compared to offenses that are longer apart.

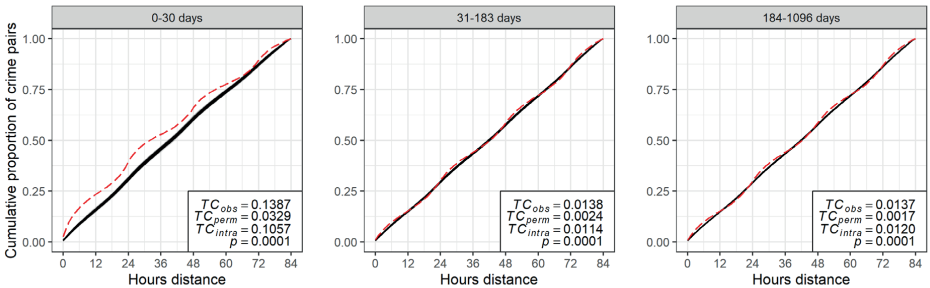


Figure 2.8 Cumulative proportions of crime pairs for hour of week within 0-30 days (left), 31-183 days (middle) and 184-1096 days (right). The hypothesis tests the *difference* between left and middle, and middle and right figures (N = 28,274 offenders).

2.5 Discussion

The aim of the present study was to examine the degree of temporal consistency in individual offending patterns. Because offenders, victims and potential guardians are all subject to temporal constraints in their daily time budget, we hypothesized offenders to show consistency in the timing of their offending by repeatedly committing offenses at similar times of day and week. We also hypothesized temporal consistency patterns to be stronger for same crime-type pairs than for pairs of different crime types, and that temporal consistency is likely to be stronger the less time has elapsed between the offenses. We analyzed the offense histories of 28,274 repeat offenders who committed a total of 152,180 offenses between 1996 and 2009 in the greater The Hague area in the Netherlands. Because temporal consistency in offending patterns could partially be due to targets and guardians having recurring spatio-temporal patterns as well as similarities in inter-offender time-use patterns, we developed a Monte Carlo permutation test to estimate the net effect of intra-offender temporal consistency.

The results showed that offenders display strong temporal consistency: offenses committed by the same offender are often at similar hours of the day and similar hours of the week, much more so than what is to be expected based on time-varying attractiveness of targets and shared time-use patterns across offenders alone. This finding corroborates Hypothesis 1. We have to note, however, that the intra-offender temporal consistency by hour of week is notably smaller than by hour of day. In line with Hypothesis 2, we found the temporal consistency to be stronger for offenses of the same type of crime than for different types of crime, especially when we look at offenders that commit either 2, 3, 4 or 5 crimes. The temporal consistency was also stronger the shorter the time span between the offenses, but only for offenses that were committed within a month, partly corroborating Hypothesis 3. Especially for hour of week, crime pairs within 0-30 days show striking temporal consistency. In contrast to our main result of Hypothesis 1, we found an overabundance of crime pairs within the month with relatively similar hours of week.

Our study highlights the importance to consider prolificacy of offenders. More than 75% of the repeat offenders in our data committed only two to five offenses. However, because our test is based on all offense pairs, which number grows quadratically with the number of offenses committed, a small number of very prolific offenders with a slightly different temporal consistency pattern will strongly affect the overall results. For this reason, we also tested the hypotheses separately for four different offender groups, i.e. those that had committed 2, 3, 4 or 5 offenses. All of our findings on the total sample are replicated in each of the analyses by offender group, but the results are much more substantively meaningful. In other words, our theoretically derived expectations are much more applicable to offenders who commit relatively few crimes (the majority in our sample) than very prolific ("career") offenders.

Our results are in line with findings from recent human mobility research. By studying the trajectories of anonymized mobile phone users for a six-month period (Gonzalez et al., 2008) or using a combination of mobile phone and GPS data (Pappalardo et al., 2015), these studies consistently showed that human behavior is generally quite regular and follows simple reproducible (temporal) patterns. The results of our study show that offenses committed by the same offender also show strongly recurring daily and hourly rhythms. These findings contribute to progress in geography of crime research. Previous studies already showed that offenders make rather consistent *spatial* decisions (for an overview, see Bernasco, 2014a), but we now show the same holds regarding their *temporal* decision-making.

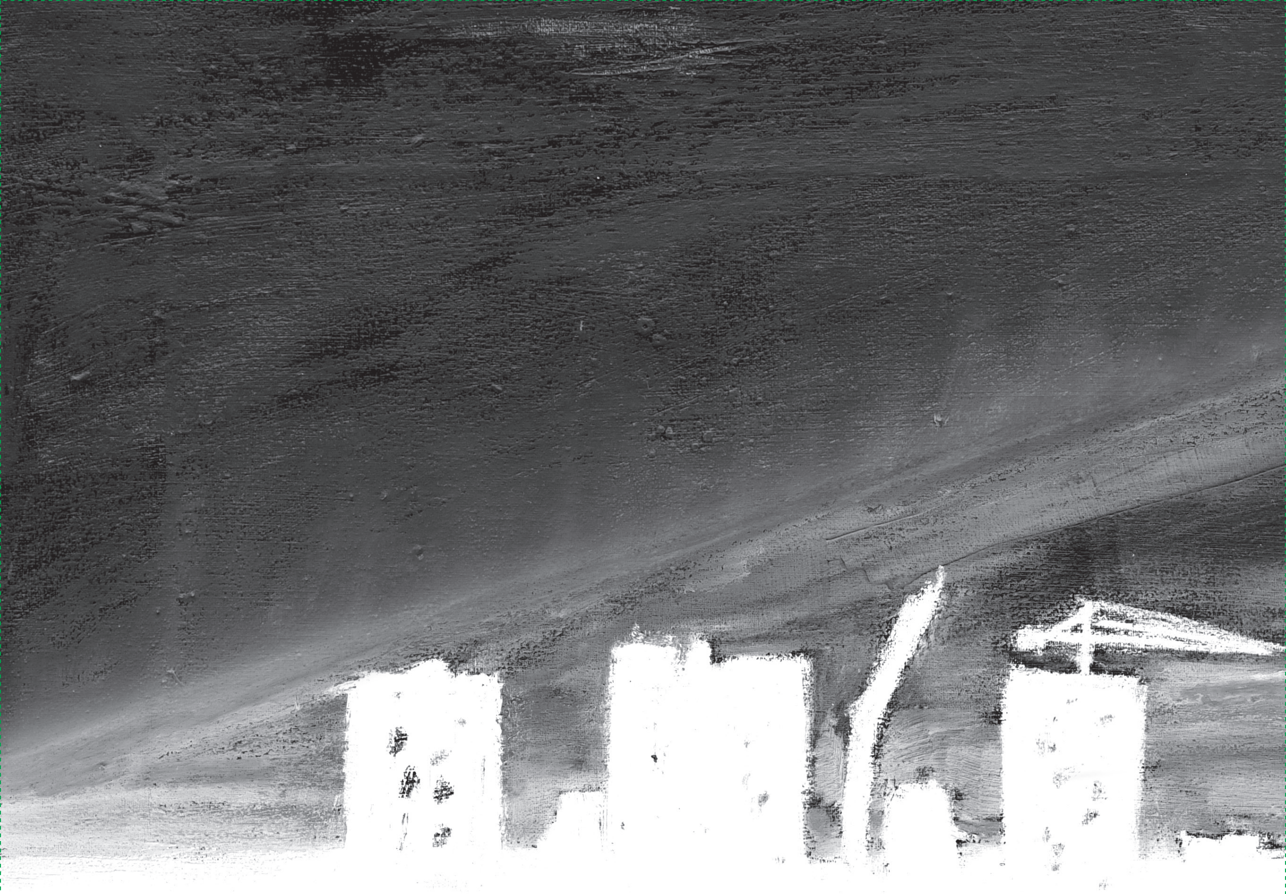
As with previous studies that used police data, an obvious disadvantage of our research design is that it only uses information on offenses that for some reason appeared in the Dutch police registration system. It is thus impossible to make inferences about the temporal patterns in offenses committed by offenders who never got caught. Although there is no satisfactory answer about the differences between the offending patterns of arrested and non-arrested offenders with regard to circular time patterns within the day or week, previous studies that compared these different offender groups were not able to find evidence for large differences in spatial offending or patterns of temporal decay (e.g., Johnson et al., 2009; Lammers, 2014; Summers et al., 2010). However, an important issue here remains possible selection bias caused by the way our sample is selected. First, our sample consists of repeat offenders who—due to the fact that they were already registered as suspects of crime in the judicial system—might have been more likely to get arrested again. Comparing arrested and non-arrested offenders in the Netherlands using DNA traces, Lammers, Bernasco and Elffers (2012) indeed found that offenders who had committed more crimes had a higher probability to be arrested again. In addition, it could be that offenders who are more consistent are even more likely to get arrested exactly because of their recurring behavior. If this is indeed the case, our study *over*estimated intra-offender temporal consistency. However, we do not have evidence that Dutch police act in such a way, at least not for high volume crimes.

On the other hand, as our sample only consists of suspects of crime rather than convicted criminals, we might also have *under*estimated intra-offender temporal consistency. An estimated 10% of the suspects from the Dutch police system HKS eventually do not get convicted (Besjes & Van Gaalen, 2008; Blom et al., 2005). This could mean that for some offenses in our analysis the wrong offender ID was assigned, because the offender originally related to the offense turned out to be innocent later on. Therefore, when we would be able to make use of actual conviction data that contain fewer such misclassifications, we would expect an even larger temporal consistency effect among convicted offenders. Also, the fact that we did not take possible co-offending into account but rather isolated offenses from individual offenders might be of influence. Specifically, we treated every offense as if it was committed by only a single offender. In reality, however, co-offenders could also have been involved with certain crimes, which means that routines activity patterns of different offenders are at play (see Lammers, 2018). As co-offending might imply a mixture of offender routines, we expect even larger consistency effects among solo-offenders.

These shortcomings notwithstanding, the present study has several practical implications. First, crime linkage procedures that identify a series of crimes as belonging to the same offender strongly rely on the spatio-temporal patterning of the crimes (e.g., Lundrigan & Canter, 2001; Markson et al., 2010; Tonkin et al., 2011). However, these methods generally rest on the assumption that crimes close in space and time are more likely to be part of a series of the same offender. In other words, crimes that occurred nearby and only a few days apart are more likely to be linked to the same offender. Our results show that this assumption might be overly simplistic: offenders are also more likely to commit crimes around the same hour of day and hour of week, even if some time has passed. Thus, our results suggest that crime linkage methods should include *periodically recurring* patterns in crime events next to the passing of linear time between the events. In a similar vein, the findings of this study could also be used for the improvement of predictive policing methods (e.g., Bowers et al., 2004; Mohler et al., 2015; Rummens et al., 2017). As in crime linkage analysis, most predictive policing applications strongly rely on spatial and temporal decay functions and they do not include cyclical time effects (for two exceptions, see Johnson et al., 2007b; Rummens et al., 2017). Hence, future predictive policing methods could benefit from combining cyclical time measures with the already existing spatio-temporal decay functions.

Lastly, it would be interesting to test whether recidivism decreases if we devise interventions aimed to disrupt an offender's temporal crime pattern. For instance, the probation service could engage them in courses or other activities that are 'temporally tailored' to the offender, specifically around those times and days the offender was previously engaged in criminal activities. If reintegration programs for offenders plan legitimate activities during the times the offenders had previously committed offenses, their opportunity for committing crime at these times is reduced. Experimental research could test whether and to what extent such an approach would be effective: in the experimental group, a probation officer would be provided with information about the time slots in which the offender should be offered alternative activities, while in the control group such information would not be provided.

To conclude, this article has shown that repeat offenders commit their crimes at similar hours of day and week over and above what is to be expected given the temporal distribution of crime events in the data due to time-varying target attractiveness and shared time-use patterns across offenders. Extending the body of research on spatial decision-making, the present study shows that studying *temporal* criminal decision-making is also of importance. Even so, we cannot make any definitive claims about *why* offenders show temporally consistent offending behavior. There are at least two potential explanations for the observed intra-individual temporal consistency in offending. First, offenders might be temporally *constrained* by their daily routines as hypothesized from time geography theory, and therefore offend at the times of day and week available to them. Second, offenders might also actively decide to change their daily routines to *create* opportunities for crime at their preferred time. For example, in their study on prolific burglars in suburban areas of Philadelphia and New York, Rengert and Wasilchick (2000) describe how a few burglars deliberately quit their legitimate jobs in order to have the opportunity to burglarize homes at the most ‘vulnerable days and times’. While our study presents empirical evidence for temporal consistency in individual offending patterns, the next step is to investigate such mechanisms.



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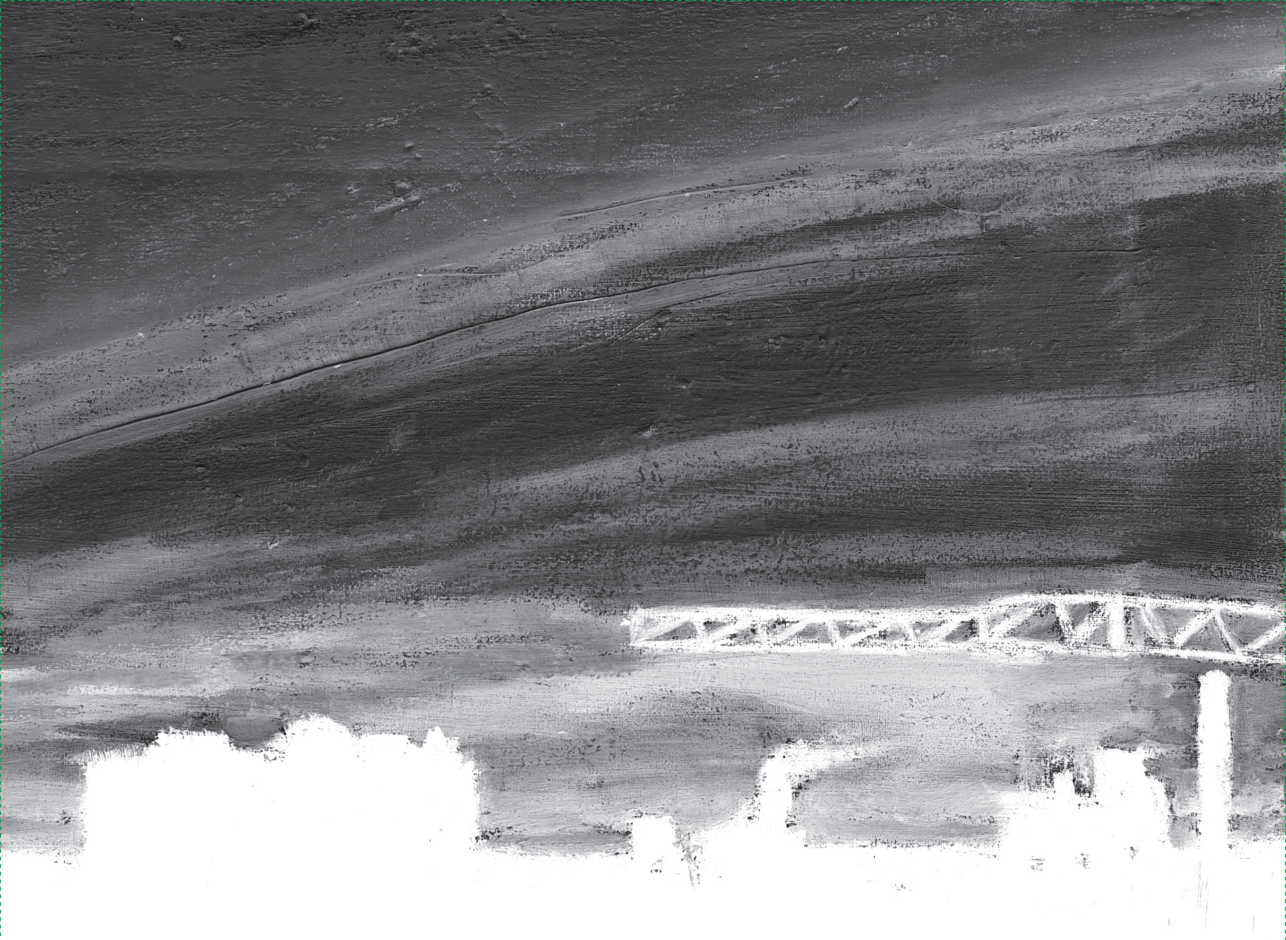


CHAPTER 3

Crime time choice: the role of discretionary and non-discretionary routine activities in temporal criminal decision-making

Abstract

Objectives. Studies on criminal decision-making often focus on where offenders commit crime, but hardly when offenders commit their crimes and why at these times and not others. The aim of the present study is to examine the relationship between the daily routine activity patterns of offenders and the timing of their crimes.

Methods. We use a unique online survey instrument in which 30 offenders reported on the specific times of the week they committed 71 offenses and routinely visited a diverse range of activity locations, such as those for work, school and leisure activities, in the year prior to the survey. We analyze the individual crime time choices of offenders using a discrete choice model and investigate the role of discretionary and non-discretionary routine activities in the temporal criminal decision-making process.

Results. Contrary to our expectations, we do not find that offenders are less likely to commit crime at times when they are usually engaged in routine activities as compared to the times when they are not. In addition, we also do not find that offenders are less likely to commit crime at times when they are routinely engaged in a non-discretionary activity than at times when they are routinely engaged in a discretionary activity.

Conclusion. This is the first study in environmental criminology that systematically combines the crime time choices of offenders of different crime types with a detailed account of their temporal routines.[12]

[12] A version of this chapter is submitted to an international scientific journal. This chapter is co-authored by S. Ruiter and W. Steenbeek.

3.1 Introduction

For a crime event to occur there has to be convergence in both space and time between a motivated offender, a suitable target and the absence of a capable guardian (Cohen & Felson, 1979; Felson, 2008). Many studies in environmental criminology have focused on the place, the victim or the role of the guardian (e.g., law enforcement). However, ultimately it is the offender who decides on where and when to commit a crime (e.g., Bernasco & Ruiter, 2014; Ruiter, 2017) and in the present study we focus on such criminal decision-making. Most criminal decision-making studies examine *where* offenders commit crime and why at these particular locations and not others. Previous research has consistently shown, for example, that most crimes are committed not far from offenders' homes (e.g., Bernasco & Nieuwbeerta, 2005; Townsley et al., 2015; Wiles & Costello, 2000). Other studies have found that their residential and offense histories are also important in explaining offenders' crime location choices (e.g., Bernasco & Kooistra, 2010; Kuralarasan & Bernasco, 2021; Lammers et al., 2015; Long et al., 2018), just like other routinely visited places, such as their schools, workplaces and leisure activities (e.g., Menting et al., 2020; Van Sleeuwen, Ruiter & Steenbeek, 2021; Chapter 5).

In stark contrast to all the attention paid to spatial criminal decision-making, the temporal aspects of offenders' crime choices have generally been overlooked. In this study, we do not ask where offenders commit their crimes, but we ask: *when* do offenders commit their crimes and why at these times instead of others? We argue that this temporal question is an important one, because routine activities can place strong temporal constraints on humans and hence offenders (Golledge & Stimson, 1997; Hägerstrand, 1970; Ratcliffe, 2006). This in turn can limit participation in other activities, such as committing crime, during certain time periods. Although several ethnographic studies already reported on offenders' routine activity patterns in relation to their criminal behavior (see e.g., Cromwell et al., 1991; Rengert & Wasilchick 2000), these studies were limited to a small-scale qualitative interview design of professional burglars. As such, their focus is on describing a few illustrative examples of a specific type of crime in high detail. The survey-based research design of the present study, although of a small sample size as well, improves upon prior qualitative research by using a more structured sampling frame, fully-structured questionnaire and a focus on general patterns instead of case to case descriptions. Therefore, the goal of the present study is to examine the relationship between the daily routine activity patterns of offenders of different crime types and the timing of their crimes. More specifically, we make a distinction between discretionary routine activities that are voluntary or less time-compulsory (e.g., shopping or going out), and non-discretionary routine activities that generally have more rigid time windows in which they are performed (e.g., going to work or attending school). We study to what extent the timing of their crimes is related to the times when offenders are routinely engaged in a variety of activities.

In the crime location choice literature (for an overview, see Ruiter, 2017; Curtis-Ham, Bernasco, Medvedev & Polaschek, 2020) only few studies have addressed temporal aspects of criminal decision-making, but the dependent variable was always the spatial choice of where to offend. For example, Bernasco et al. (2017) studied whether robbery location choice criteria, such as the presence of small businesses and high schools or distance from home, impact the offenders' location choices differently over the course of the day and over days of the week. They only found the effect of high schools to vary temporally while all other robbery location choice criteria had the same effects throughout the day and week. Van Sleeuwen et al. (2018; Chapter 4) showed that offenders are more likely to return to previously targeted areas when the previous offense was committed on the same day of the week and at the same hour of day. Van Sleeuwen et al. (2021; Chapter 5) generalized this idea by claiming that offenders are not only more likely to return to previously targeted areas at specific times, but they are also more likely to commit crime in neighborhoods they have regularly visited at the same time of day than in neighborhoods they have regularly visited at different times of day.

Importantly, these studies did not consider the timing of the crime itself as an individual offender choice—and thus these studies did not consider the timing of the crime as the outcome variable—but rather as a condition affecting their spatial decision-making. In this study, we analyze the timing of crime as an offender choice using a discrete choice model and we look at how these temporal choices are related to offenders' discretionary and non-discretionary routine activities. To our knowledge, this is the first study in environmental criminology that systematically combines offenders' crime time choices with a detailed account of their temporal routine activity patterns.

3.2 Theoretical framework

The convergence of a motivated offender, suitable target and absence of a capable guardian (Cohen & Felson, 1979; Felson, 2008) is argued to be a function of the non-criminal routine activity patterns of offenders and those of potential targets and guardians. Although all these elements can be seen as necessary conditions for a crime to happen, the focus here is on the former; the offenders and their daily routine activities. Routine activities are defined as "any recurrent and prevalent activities which provide for basic population and individual needs, whatever their biological or cultural origins" (Cohen & Felson, 1979; p. 593), such as work, schooling, leisure time, childrearing and social interaction. According to Hägerstrand's (1970) time geography framework (also see Golledge & Stimson, 1997; Ratcliffe, 2006), routine activities can place strong temporal constraints on humans, which in turn can limit participation in or restrict access to other activities during certain time periods. Hägerstrand (1970) argues that, for example, so-called 'capability constraints' occur because of biological constraints and physiological necessities that every human being faces (such as eating and resting), while 'coupling constraints' are related to all activities and interactions needed for institutional demands (e.g., work, school) and personal obligations (e.g., childcare). As Hägerstrand puts it:

> "*These [constraints] define where, when, and for how long, the individual has to join other individuals, tools, and materials in order to produce, consume, and transact*." (Hägerstrand, 1970; p. 14)

Applied to criminal decision-making, offenders' daily routine activities therefore largely determine their exposure to criminal opportunities. Put simply, when offenders are busy with other activities, they cannot commit crime. Our first hypothesis thus reads:

> ***Hypothesis 1***: Offenders are less likely to commit crime at times when they are usually engaged in routine activities as compared to the times when they are not.

The time geography framework states that human activity systems consist of two different *types* of activities (Golledge & Stimson, 1997; Rengert & Wasilchick, 2000); (1) activities that are performed by choice (i.e., voluntary or discretionary activities) and (2) activities that have to be undertaken (i.e., obligatory or non-discretionary activities). Examples of discretionary activities include recreation, shopping and leisure, while non-discretionary activities encompass the necessity to sleep, go to work, and attending school. Non-discretionary routine activities have more rigid time windows in which they need to be performed, which force people to perform these activities at specific times.[13] In contrast, many recreational activities such as going to a restaurant, bar, club or sports center are less compulsory, and therefore "have a lesser temporal rigidity in the daily life of an offender" (Ratcliffe, 2006; p. 264). Because of its

[13] While work and school are of course not as obligatory as eating or sleeping, we still consider these activities as non-discretionary rather than discretionary.

compulsory character and the relatively large amount of time non-discretionary activities generally require, they really shape the rhythm of people's daily life and determine the degree of flexibility and possibilities for discretionary activities. Applied to criminal decision-making, an offender with a daytime job has less time to commit (non-workplace) crime during his working hours than an offender that usually spends those hours of day on shopping or other leisure activities. The discretionary nature of these latter activities allows more flexibility to change plans and commit crime instead. Hence, we formulate our second hypothesis:

> ***Hypothesis 2***: Offenders are less likely to commit crime at times when they are routinely engaged in a non-discretionary activity than at times when they are routinely engaged in a discretionary activity.

3.3 Data and methods

3.3.1 Time-specific Activity Space (TAS) survey

We collected data in 2019 from a sample of police suspects from two Dutch police regions (The Hague and North-Holland) using the Time-specific Activity Space (TAS) survey that we developed ourselves. In order to be included in our sample, a suspect needed to have at least one recorded offense in 2017 that was filed to the public prosecutor, be 18 years or older at the time of the sample selection and have a valid home address in the Dutch information system on residential addresses (in Dutch: "Basis Registratie Personen [BRP]"). Respondents were approached by sending them an initial invitation letter with login details for accessing the online survey and a reminder letter after 1.5 weeks. The beginning of the survey encompassed a detailed information page about the research project, the contents of the questionnaire, a privacy statement and informed consent form. By the end of August 2019, 363 respondents were sent a gift card of 25 euro for fully completing the survey. 30 of these respondents reported having committed at least one crime in the year prior to the survey. In total, these thirty respondents reported on 71 unique crimes and 155 different activity nodes in the year prior to the survey.

In the first part of the TAS survey, respondents were asked to report on their routine activity locations, categorized in seven different domains: (1) homes, (2) schools, (3) jobs, (4) sports activities, (5) shopping, (6) going out, and (7) any other activity location that the respondents could specify themselves. For each domain, the respondents were asked to indicate whether they had visited such an activity node approximately every week—our definition of "routinely"—over the past year. If so, they were asked to indicate the locations of these routine activity nodes on an interactive map, for a maximum of six locations per domain. For each of these locations, respondents indicated during which days of the week and times of the day they had routinely visited that location in the past year. We presented this as a 7 (days of the week) by 8 (3-hour time slots per day) matrix to the respondent (per day, the eight possible time slots of three hours each started from midnight-3 a.m. and ended at 9 p.m.-midnight).

The second part of the survey asked respondents whether and where they had committed the following crime types in the past year: (1) residential burglary, (2) theft of/from a bicycle, car or other (motor) vehicle, (3) theft from a shop/shoplifting, (4) theft (of an object) from a person, (5) robbery, (6) assault, and (7) vandalism. For up to three incidents per crime type, we asked respondents to provide additional temporal details, comparable to the survey questions regarding their routine activities: on which day of the week and 3-hour time slot the crimes were committed. For each of the seven activity domains as well as for each reported crime type, respondents were also asked to indicate the accuracy of the reported days and times (i.e., very accurate, reasonably accurate, reasonably inaccurate, very inaccurate).

In order to determine the adequate temporal resolution for our unit of analysis, we first investigated the reported level of temporal accuracy for the seven routine activity domains and the different types of crime. For more than eighty percent of the reported times in the survey, the respondents indicated the timing of their routine and criminal activities to be reasonably or very accurate. Hence, we decided to use the original 3-hour time slices as the temporal resolution: seven days of the week comprising each of eight different 3-hour time slots, ranging from midnight-3 a.m. to 9 p.m.-midnight, for 7*8 = 56 time slots in total.

3.3.2 Variable construction

The 30 offenders altogether reported to have committed 2 residential burglaries, 9 thefts of/from a bicycle, car or other (motor) vehicle, 40 thefts from a shop/shoplifting, 14 assaults, and 6 acts of vandalism over the past year (71 offenses in total). In order to perform our analyses, we created a dataset of 56 different times slots nested within each offense. The dependent variable *crime committed at time slot* (1 = yes; 0 = no) indicates whether or not an offense was committed during one of the 56 possible time slots in the week. For the independent variables, we created seven dichotomous variables to indicate whether the offender had been routinely engaged in each of the seven different routine activity domains during the prior year, per time slot. For example, the independent variable *routinely spent time at work* (1 = yes; 0 = no) indicates whether or not the respondent was routinely engaged in spending time at work during a specific 3-hour time slot. As the offenders could have reported to be routinely engaged in different routine activity domains within one 3-hour time slot (e.g., one hour for shopping and the second two hours for going to school), these variables are not mutually exclusive. For Hypothesis 2, regarding the relationship between engagement in (non-)discretionary routine activities and crime, we operationalize the domains of *home*, *sports*, *shopping, going out*, and *other activity* as discretionary activities (imposing fewer constraints on the offenders' time) and *work* and *education* as non-discretionary activities (imposing more constraints on the offenders' time).

3.3.3 Methods

To test our hypotheses regarding the crime time choices of offenders, we estimated a conditional logit model as commonly applied in crime location choice research (e.g., Bernasco & Ruiter, 2014; Ruiter, 2017), but with a temporal rather than a spatial choice set. The choice outcome is the time slot in which the offender committed the offense. Because each of the 71 offenses could have been committed in any of the 56 time slots in the week, our final dataset for analysis consists of 3,976 rows (56 rows of time slots for each of the 71 reported crimes). As the small sample size does not justify using normal standard errors, we calculated bootstrapped standard errors based on 100 samples. These standards errors were also cluster-corrected because 30 offenders committed the 71 offenses. The results of the conditional logit models are presented using odds ratios (ORs) and their respective bootstrapped cluster-corrected standard errors (SEs). All the independent variables have a value of 0 when the offender was *not* usually engaged in any routine activity for a specific time slot (i.e., the reference category).

To check for the robustness of the results, we performed several additional analyses. First, recall that the convergence of a motivated offender, suitable target and absent capable guardian in space and time is a function of both the routine activity patterns of offenders and those of potential targets and guardians. Regarding the latter, opportunity structures are clearly crime-specific. For example, a residential area is more attractive for burglary during the day than during the night, due to a lack of surveillance during daytime when residents and neighbors are usually away from home (e.g., Coupe & Blake, 2006; Wright & Decker, 1994). In contrast, potential victims on the street in combination with few guardians around are ideal circumstances for street robbery, such as during late evening hours in the weekend when people go home after a night out. Although motivated offenders and attractive targets are necessary conditions for a crime to happen, and the latter might be time-varying depending on crime type, in the present study we combine all crime types and focus on offender routines. Regardless of the time-varying attractiveness of targets, offenders can only offend in the time available to them, which is constrained by their non-discretionary and discretionary routine activities: therefore we expect that our hypotheses hold across crime types. To investigate this, the analyses were repeated using five different samples in which one of the different crime types was omitted for each sample (see Table 3.3 in the Appendix, only substantively different results are shown). In addition, we repeated the analysis with a sample in which the hours during the night that were routinely spent at home were removed (i.e., the time slots 00.00-03.00 and 03.00-06.00 for each day of the week), because we assume most offenders will have spent these hours sleeping if at home and thus not able to commit a crime (see Table 3.4 in the Appendix)[14].

3.4 Results

3.4.1 Time spent at different routine activities

For each of the 56 3-hour time slots of the week, Figure 3.1 shows the percentage of offenders that reported being routinely engaged in a certain activity domain during that particular time slot. We observe, for example, that the percentage of offenders that routinely spent time at home is higher during the evening and night than during the day, while the percentage of offenders that routinely spent time at work or school peaks during the day on Monday to Friday (mostly between time slots 06.00-09.00 to 15.00-18.00). In addition, the most popular time slots for going out are in the evening and night on weekends days (mostly between time slots 21.00-00.00 to 03.00-06.00). The overall routine activity patterns of the offenders observed in Figure 3.1 resemble general time-use patterns of the Dutch population (e.g., Cloïn et al., 2013). Using a time-use diary survey, Cloïn et al. (2013) estimated the percentage of Dutch people that are in bed at home around midnight and at 1 a.m. in the morning during the week at about 80% and 95% respectively. This is comparable to the percentages of offenders in our study that reported to have routinely spent time at home between time slot 00.00-03.00 for the different weekdays.

[14] This is an assumption because the variable *routinely spent time at home* only indicates whether or not the respondent routinely spent time at the home location at a particular time slot, but not—if he was indeed at home between midnight and 6 a.m.—whether he was usually asleep during that time.

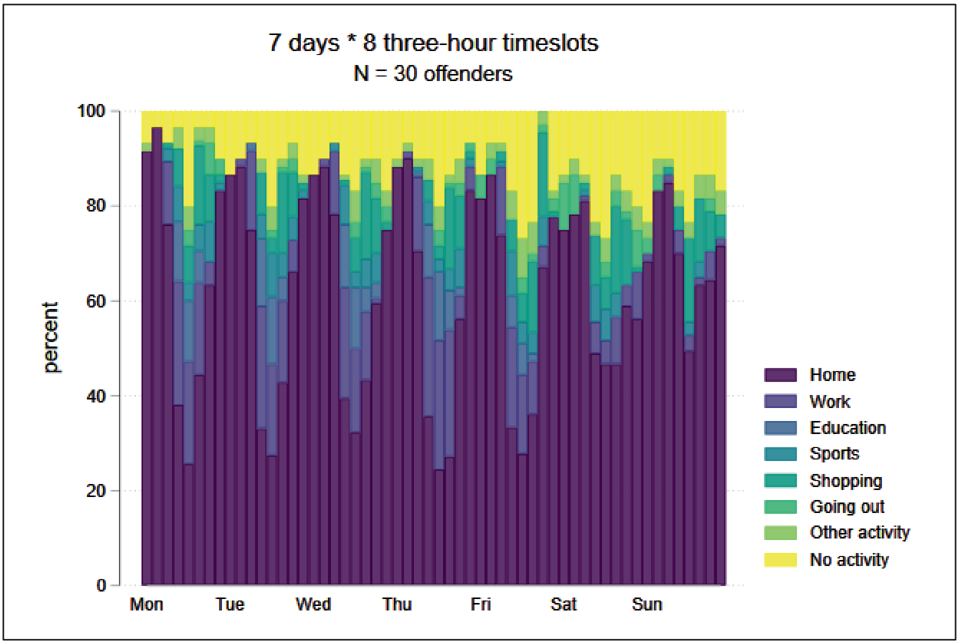


Figure 3.1 Percentage of offenders that reported being routinely engaged in a certain activity domain for each of the 56 3-hour time slots of the week (starting at Monday 00.00-03.00)[15].

3.4.2 Relation between routine activity domains and offending

Almost half of the offenses (i.e. 34 of the 71) were committed at a 3-hour time slot in which the offender reported to be routinely engaged in only one routine activity domain. In contrast, 26 of the offenses were committed at a 3-hour time slot in which the respondent was routinely engaged in multiple activity domains: for 18 and 8 offenses, the offenders were routinely engaged in two or three different activity domains respectively at that specific crime time slot. Lastly, 11 of the 71 offenses were committed at a time slot in which the offenders did not report routinely performing any activity.

Table 3.1 shows the bivariate relations between the different routine activity domains and offending per 3-hour time slot ($N = 71$ offenses committed by 30 offenders). As more than one-third of the offenses are committed during a time slot in which the offenders reported being routinely engaged in multiple routine activities, the total sum of all activities (i.e., the number of offenses with 'yes' after a specific activity domain) in the table is higher than 71. The

[15] In about one-fifth of the cases, respondents reported to be routinely engaged in multiple activity domains at a single time slot. In these instances, we divided the count ('1') for each activity by the total number of domains during that time slot (range 0.25, 0.33, 0.50).

absolute number of offenses is shown in the first column. For example, more than half of the 71 offenses (i.e. 40) were committed during a 3-hour time slot in which the offender routinely spent time at home (either exclusively or combined with another activity domain during that time slot, see above), while only three offenses were committed during a time slot in which the offender routinely spent time at education.

Table 3.1 Bivariate relations between routine activity domain and offending per 3-hour time slot (N = 71 offenses committed by 30 offenders).

Variable	Number of offenses	Number of 3-hour time slots	Percentage of 3-hour time slots	Number of offenses per 1,000 hours
Routinely spent time at/on ...				
... Home				
No	31	1,211	30.46	8.53
Yes	40	2,765	69.54	4.82
... Work				
No	59	3,437	86.44	5.72
Yes	12	539	13.56	7.42
... Education				
No	68	3,880	97.59	5.84
Yes	3	96	2.41	10.42
... Sports				
No	63	3,749	94.29	5.60
Yes	8	227	5.71	11.74
... Shopping				
No	49	3,666	92.20	4.46
Yes	22	310	7.80	23.66
... Going out				
No	67	3,816	95.98	5.85
Yes	4	160	4.02	8.33
... Other activity				
No	66	3,810	95.82	5.77
Yes	5	166	4.18	10.04
... No activity				
No	60	3,341	84.03	5.99
Yes	11	635	15.97	5.77
Total	71	3,976	100	5.95

Note: as more than one-third of the offenses are committed at a time slot in which the offenders reported being engaged in multiple activity domains, the total sum of all activities (i.e., the number of offenses with ‘yes’ after a specific activity domain) is higher than 71.

The second and third column display the total number and percentage of 3-hour time slots in the data for each of the activity domains in the first column. For example, out of the 3,976 possible 3-hour time slots of the week, the offenders reported to have routinely spent time at home for 2,765 time slots (69.54%), while routinely spending time in educational activities for only 539 of the time slots (13.56%). The final column in Table 3.1 lists the number of offenses committed per 1,000 hours. It shows that the offenders in our data commit 4.82 offenses per 1,000 hours in time slots in which they routinely spent time at home (40 / 2,765 * 1000 / 3), while 10.42 offenses per 1,000 hours are committed at time slots in which the offenders routinely spent time in educational activities (3 / 2,765 * 1000 / 3). We also observe that although the offenders did not spend that many 3-hour time slots shopping (less than 8%), they committed a relatively large number of crimes during a time slot in which they reported being routinely engaged in shopping (23.66 offenses per 1,000 hours).

3.4.3 Offenders' crime time choices

Table 3.2 presents the results of the conditional logistic regression model with bootstrapped standard errors for our hypotheses tests. It shows the association of engagement in different routine activity domains and the offenders' crime time choices (*N* = 71 crimes * 56 possible 3-hour time slots of the week = 3,976). The reference category (i.e., when all independent variables have a value of 0) represents the situation in which the offender was not usually engaged in any routine activity domain during a specific time slot.

Table 3.2 Conditional logit model testing the association of different routine activity domains and offenders' crime time choices (*N* = 71 crimes * 56 possible 3-hour time slots of the week = 3,976).

Variable	**OR**	**SE**	**Z**	**P**
Routinely spent time at/on ...				
... Home	0.541	0.258	-1.29	0.198
... Work	1.205	2.867	0.08	0.937
... Education	1.845	3.999	0.28	0.777
... Sports	1.879	4.757	0.25	0.803
... Shopping	5.906	2.870	3.65	0.001
... Going out	1.159	6.723	0.03	0.980
... Other activity	1.727	7.665	0.12	0.902
Pseudo-R^2	.08			

Note: OR = odds ratio coefficient; SE = bootstrapped cluster-corrected standard error; Reference category (if all study variables score 0) = offender is not usually engaged in any routine activity during specific time slot.

We expected that offenders are less likely to commit crime at times when they are usually engaged in routine activities (Hypothesis 1), and thus the odds ratios for the seven study variables to be smaller than 1. Contrary to our expectations, the odds ratios for all the different routine activity variables except for *routinely spent time at home* are all greater than one, and only the odds ratio for the variable *routinely spent time on shopping* is statistically significant. The joint test of all activities combined (i.e. routine activity versus no routine activity) shows that offenders are not less likely to commit crime at times when they are usually engaged in routine activities as compared to the times when they are not (OR = 1.045, p = 0.929). Therefore, our results do not corroborate Hypothesis 1.

We also hypothesized that offenders would be less likely to commit crime at times when they are routinely engaged in a non-discretionary rather than a discretionary activity (Hypothesis 2). Therefore, we expect the odds ratios for the non-discretionary activity variables to be smaller than the odds ratios for the variables regarding discretionary activities. Table 3.2 seems to lend some support to this expectation, as the estimated odds ratio for the non-discretionary activity domain *work* is lower than that of the discretionary activity domain *sports*, *shopping* and *other activity* and comparable to the odds ratio of *going out*. The odds ratio for the non-discretionary *education* is only lower than that of *sports* and *shopping*. However, a Wald Chi-Squared test of the difference between the two joint subgroups (i.e. *work* and *education* versus *home*, *sports*, *shopping*, *going out*, and *other activity*) shows that offenders are *not* less likely to commit crime at times when they are routinely engaged in a non-discretionary activity (OR = 1.524) than at times when they are routinely engaged in a discretionary activity (OR = 1.101) ($\chi^2(1)$ = 0.24, p = 0.625).

As discussed in more detail in the Methods section, as a first robustness check, we repeated the analyses using five different samples, each time excluding one of the crime types. Table 3.3 (see Appendix) shows that when we exclude the 40 shoplifting events from the analysis, the odds ratio for the variable *routinely spent time on shopping* becomes statistically non-significant. The conclusions with regard to our hypotheses remain unchanged. Repeating the analysis with all hours spent at home during the time slots between 00.00-03.00 and 03.00-06.00 removed, we observe in Table 3.4 (see Appendix) that the overall results are quite similar to those presented in Table 3.2.

3.5 Discussion

The question why offenders commit crime at certain times and not others has to date remained rather under-studied in the environmental criminology literature. The goal of the present study was to examine daily routine activity patterns of offenders and how these are related to the timing of their crimes. Building on Hägerstrand's (1970) time geography, we proposed a relation between offenders' general time-use patterns and the (in)ability to perform criminal activities at certain times. Data were collected using a unique online survey instrument we developed in which 30 offenders reported on the specific times they had committed 71 offenses and routinely visited a diverse range of activity locations, such as those for work, school and leisure activities, in the year prior to the survey. We applied a discrete choice model to investigate the relationship between the routine timings of certain discretionary and non-discretionary activities and the times at which offenders committed their crimes. Contrary to our expectations, offenders were not less likely to commit crime at times when they are usually engaged in routine activities as compared to the times when they are not. The results thus lend no support for the idea that daily routine activities prevent offenders from committing crime.

The results are not consistent with our expectations based on time geography (Golledge & Stimson, 1997; Hägerstrand, 1970), in which people's daily routines are viewed as temporal constraints on their behavior. We expected that if offenders are too busy with their routine activities they would not have time for committing crime, but our data do not support this expectation. In Chapter 1 and in the two crime location choice studies of this dissertation (Chapter 4 and Chapter 5), we developed an extension of crime pattern theory that may offer an alternative explanation for these surprising findings. After all, during daily routine activities offenders acquire time-specific knowledge about criminal risks, rewards and opportunities in their spatial environment. This makes them most likely to commit crime at the times of day those areas were previously targeted (Van Sleeuwen et al., 2018; Chapter 4) or routinely visited (Van Sleeuwen et al., 2021; Chapter 5). As routine activities provide offenders with the relevant knowledge about criminal opportunities, it is perhaps because of this time-specific knowledge that they prefer to commit their crimes at times when they usually perform routine activities over the times without daily routines. To move forward with these theoretical considerations, in future research a more specific research design is needed that is able to measure the degree of knowledge about target attractiveness at different times of the day and week.

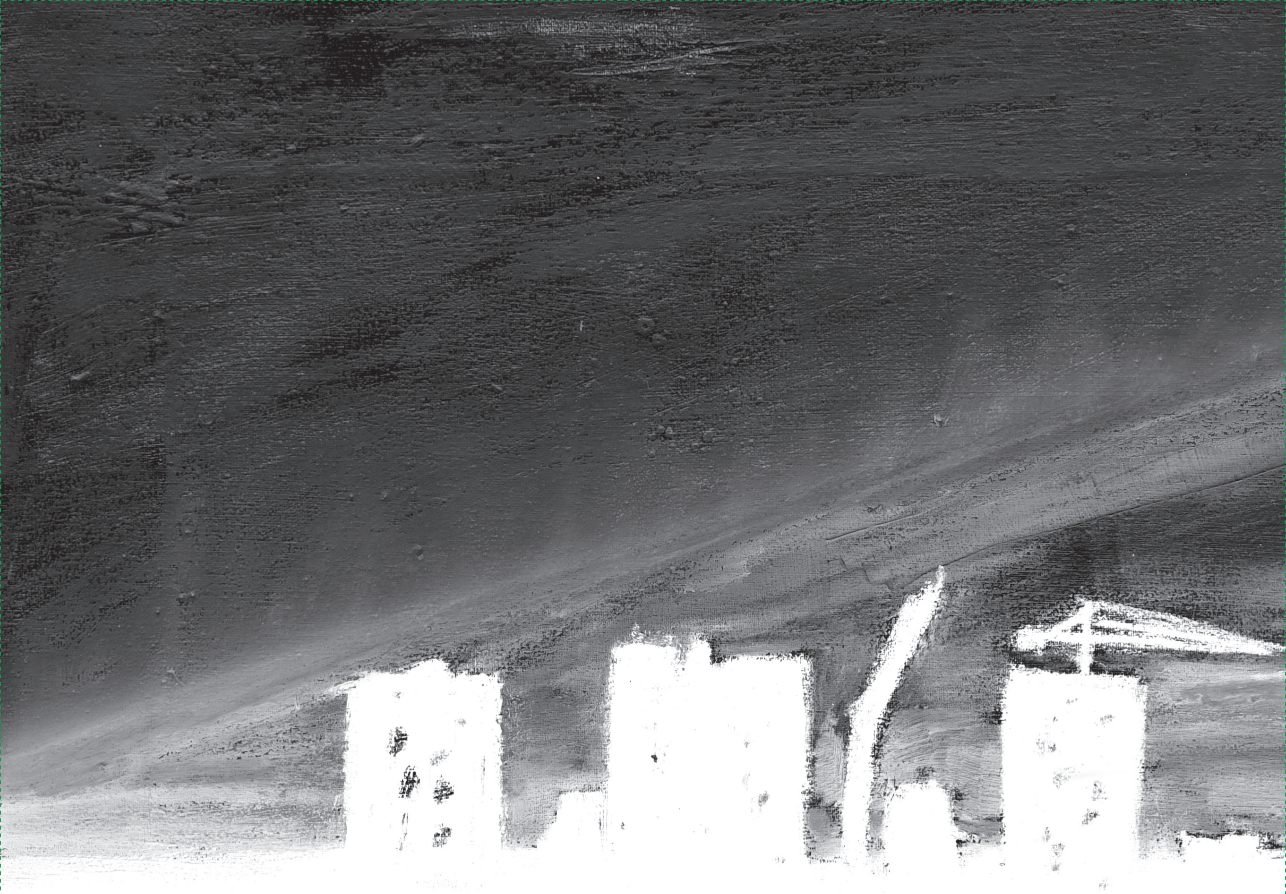
We checked for the robustness of the results by performing several additional analyses. As argued before, the timing of offenses depend on (1) offender-specific characteristics (related to their time-use) and (2) target-specific characteristics (related to time-varying attractiveness). The finding that our results are not completely robust for the specific types of crime involved, indicates that it is important to think about the time-varying attractiveness of potential targets next to offender routines. Unfortunately, we were not able to investigate how the (crime-type specific) attractiveness of targets varies over the course of the day and day of the week in the present study. In order to examine both elements together in future research, additional data on the characteristics of the alternatives in the temporal choice set for specific crime types are needed, such as opening and closing times of shops and businesses (e.g., for shoplifting or commercial robberies) or detailed information on crowds and residents (e.g., for pickpocketing or residential burglary).

Next to the discussion of theoretical considerations, several methodological limitations should be mentioned. A first methodological drawback of the study is that our offender sample might be too small to identify the effect size of interest. Although more than 363 respondents who were sampled from the police suspect database fully completed the online questionnaire, only 30 reported to have committed at least 1 crime in the year prior to the survey (71 unique crimes in total). A related point of caution is the unequal distribution of the different types of offenses under study. For example, the 30 offenders in our survey reported to have committed only 2 residential burglaries, but 15 assaults and 40 thefts from a shop.

Another important methodological limitation is that the temporal resolution of our data did not enable us to look at a smaller temporal scale than 3-hour time slots. More than one-third of the offenses were committed at a time slot in which the offenders reported being routinely engaged in multiple activities, but we have no information about within time slot heterogeneity. For example, when a respondent indicated to have routinely spent time on both shopping and exercising at a specific 3-hour time slot in the questionnaire, does he do his groceries before or on the way to back to the sports center? In fact, many different things can happen in a 3-hour time slot and this temporal resolution used may have led to erroneous assumptions that a crime was committed during a routine activity rather than before or after within the general 3-hour period. An alternative for future studies might be asking respondents to fill out temporal questions on a higher temporal resolution, e.g., every single hour of the week (i.e. 168 hours instead of 56 time slots). Although this might be overburdening the respondents and potentially leading to higher non-response, it would enable to test and compare different lengths of time slots (e.g., 1-hour, 2-hours), as well as different temporal boundaries around these time slots. Another option is to have the respondents fill out their own average diary themselves, after which the classification in time slots takes place.

A final methodological remark is that following the aim of this study, we do ask exactly at what day of week and time of day the offenders committed their crimes in the year prior to the survey, but not their routine activities *during* that specific day or week. Instead, our measurement of an offender's routine activities over the course of the week is based on the time spent at their routine activity nodes that they visited approximately every week during the previous year. Hence, the measurement of routine activity behavior is at the expense of not having a very detailed account of a specific set of activities at certain times around the actual crime. We therefore cannot make a 1-to-1 link between (non-)discretionary activity and crime time choices. This methodological disconnect can be resolved in future studies by shifting the focus to situational designs that directly combine offenders' daily time-use with their criminal activities, such as the space-time budget method (see e.g., Wikström, Ceccato, Hardie & Treiber, 2010; Wikström, Oberwittler, Treiber & Hardie, 2012). This method examines the respondent's whereabouts using an hour-to-hour diary for a few of days in the previous week (Bernasco et al., 2013). However, a drawback of such data collection methods is that crime is a rare event, and thus a lot of very detailed week-to-week activity patterns will be collected but with relatively few crimes (remember that the 363 respondents from our high-risk sample reported on having committed 71 offenses in total over the past *year*). Because it is difficult to get respondents to fill in their time-use and criminal activity patterns for such a long period of time (as is aimed for in this study), future research might need to resort to unobtrusive tracking methods (e.g., Rossmo et al., 2012; Ruiter & Bernasco, 2018), based on which time-specific activity and crime patterns can be reconstructed over longer time periods.

Acknowledging these shortcomings, to our knowledge this is the first study in environmental criminology that systematically combines the crime time choices of offenders of different crime types with a detailed account of their temporal routine activity patterns, i.e. time routinely spent at certain discretionary and non-discretionary activities at the same time slot. Whereas most studies that applied the discrete choice approach to criminology after Bernasco and Nieuwbeerta (2005) focused on spatial choices and consequently used location as the dependent variable, in the present paper we focused on the *temporal* criminal decision-making and modelled the crime time as a choice made by the offender from a choice set of possible times during the week. While spatial location choice studies have consistently shown that the locations offenders regularly visit are predictive of where they commit crime, we do not find evidence for the expectation that the times offenders are usually engaged in (non-)discretionary routine activities are predictive of the specific times of day they commit their crimes.



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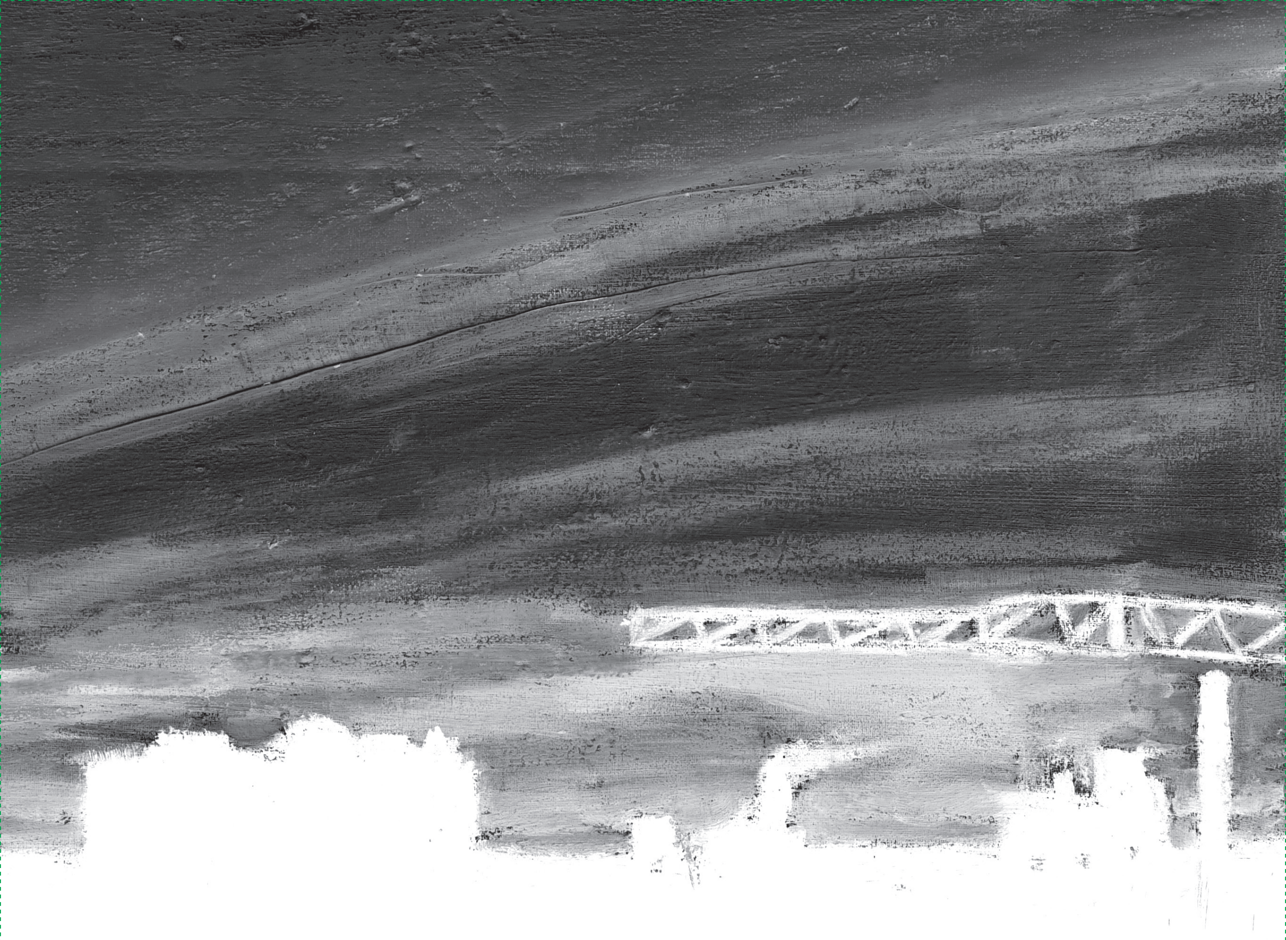


CHAPTER 4

A time for a crime: temporal aspects of repeat offenders' crime location choices

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 never targeted before. The effects were stronger for the same than for different types of crime.

Conclusion. Assessing cyclical time patterns in crime location choice not only enhances our understanding of spatial criminal decision-making, but could also improve predictive policing methods.[16]

[16] A version of this chapter is published as: Van Sleeuwen, S. E. M., Ruiter, S. & Menting, B. (2018). A time for a crime: temporal aspects of repeat offenders' crime location choices. *Journal of Research in Crime and Delinquency*, 55(4), 538-568. https://doi.org/10.1177/0022427818766395.

4.1 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 & Johnson, 2005; Farrell et al., 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 et al., 2009). Two recent studies tested this explanation using an offender perspective (Bernasco et al., 2015; Lammers et al., 2015). Following crime pattern theory (Brantingham & Brantingham, 1981; 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 et al., 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 spatio-temporal studies outside the crime location choice framework already showed the importance of cyclical time patterns across weeks (e.g., Andresen & Malleson, 2015; Johnson et al., 2012) and over the course of the day (e.g., Haberman & Ratcliffe, 2015; Sagovsky & 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.

4.2 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 & 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 & Ruiter, 2013; Clarke & 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 & 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 & 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 cyclical 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 in Wright & Decker, 1994; p. 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 & Blake, 2006) and whether neighbors that could oversee the property were at home at the time of the offense (Rengert & Wasilchick, 2000; Wright & 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.

4.3 Data and methods

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 & Gottheil, 1984; Hesseling, 1992) or potential targets (Hakim, Rengert & Shachmurove, 2001; Sampson & 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 & 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 & 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; p. 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 & Nieuwbeerta, 2005; Clare, Fernandez & Morgan, 2009; Townsley et al., 2015).

4.3.1 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 b 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 & 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, Volker, Flap & Van Oort, 2012).

4.3.2 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.

4.3.3 Measurements

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 versus 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 6-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 4.1 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 6-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 0-hour difference*. Because all dayparts consist of 6-hour time periods, the variables *previous crime location on same daypart with a greater than 6-hour difference* and *previous crime location on different daypart with a 0-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 4.2), 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 4.3).

Table 4.1 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	Minimum	Maximum	N
Timing of crime within the week					
Previous crime location on					
Same part of the week (weekend)					
Same weekend day	0.002	—	0	1	1,787,105
Different weekend day	0.001	—	0	1	1,787,105
Same part of the week (week)					1,787,105
Same weekday	0.003	—	0	1	
Different weekday	0.009	—	0	1	1,787,105
Different part of the week					
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- to 2-hour difference	0.005	—	0	1	1,787,105
3- to 5-hour difference	0.002	—	0	1	1,787,105
Different daypart with					
1- to 2-hour difference	0.002	—	0	1	1,787,105
3- to 5-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	0.172	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	0.023	42.844	142
Number of employees (per 1,000)	3.440	3.554	0.002	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 6-hour time periods, the variables *previous crime location on the same daypart with a greater than 6-hour difference* and *previous crime location on different daypart with a 0-hour difference* do not yield any scores and are therefore left out of the table.

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 start and end date) and times (i.e., no differences between the start and end 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 4.3).

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 4.1 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 & 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 0.49 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 & Block, 2011; Bernasco & Nieuwbeerta, 2005; Cohen & 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 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 4.1). 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).

4.3.4 Methods

Conditional logit models[17] 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.[18] The results of the conditional logit models are presented using odds ratios (ORs) and their respective standard errors (SEs). The ORs 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

[17] Although the more flexible mixed logit model was recently used (Frith et al., 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.

[18] 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.

positive with ORs greater than 1. More important for testing our hypotheses, differences between ORs were tested using Wald's Chi-Square difference tests. These tests reveal whether the ORs 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 SEs were estimated.

4.4 Results

4.4.1 Timing of crime within the week

After estimating a baseline model with the control variables only (Model 0, Table 4.2), the first hypothesis was tested. Model 1 in Table 4.2 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, $p < 0.001$). When committing an offense on a *different weekend day*, offenders are still more likely to return to a previously targeted area, although the odds ratio (OR = 2.93, $p < 0.001$) is statistically significantly smaller ($\chi^2(1) = 41.18$, $p < 0.001$). 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 ($\chi^2(1) = 1.52$, $p = 0.218$). 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 ORs regarding offenses committed in the same part of the week, both during the workweek and or during the weekend ($\chi^2(1) = 73.72$, $p < 0.001$). 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.

Table 4.2 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 (N = 1,787,105 offense-alternatives for 12,639 repeat offenses, committed by 3,666 offenders).

Variable	Model 0 Control variables only		Model 1 Timing of crime within the week (H1a)		Model 2 Timing of crime within the day (H1b)	
	OR	*SE*	*OR*	*SE*	*OR*	*SE*
Timing of crime within the week						
Previous crime location on						
Same part of the week (weekend)						
Same weekend day			6.384***	(0.551)		
Different weekend day			2.930***	(0.328)		
Same part of the week (week)						
Same weekday			4.256***	(0.253)		
Different weekday			3.815***	(0.171)		
Different part of the week						
Different week part			3.023***	(0.133)		
Timing of crime within the day						
Previous crime location on						
Same daypart[a] with						
0-hour difference					9.384***	(0.620)
1- to 2-hour difference					4.799***	(0.250)
3- to 5-hour difference					3.674***	(0.253)
Different daypart with						
1- to 2-hour difference					5.158***	(0.447)
3- to 5-hour difference					4.361***	(0.248)
>6-hour difference					3.378***	(0.141)
Control variables						
Current or former residence	6.177***	(0.282)	3.465***	(0.137)	3.377***	(0.134)
Distance from current residential area	0.694***	(0.007)	0.731***	(0.005)	0.733***	(0.005)
Proportion non-Western residents	2.392***	(0.197)	2.322***	(0.163)	2.292***	(0.160)
Proportion single-person households	1.525**	(0.235)	1.897***	(0.245)	1.894***	(0.244)
Population density (per 1,000)	0.992**	(0.003)	0.993**	(0.002)	0.993**	(0.002)
Number of employees (per 1,000)	1.031***	(0.004)	1.027***	(0.003)	1.026***	(0.003)
Retail business (per 10)	1.050***	(0.006)	1.036***	(0.005)	1.035***	(0.004)
Hotels, restaurants and bars (per 10)	1.011*	(0.011)	1.016*	(0.008)	1.016*	(0.008)
Schools (per 10)	1.073**	(0.028)	1.043*	(0.024)	1.054*	(0.024)
Health-care facility (per 10)	0.949***	(0.014)	0.974*	(0.013)	0.974*	(0.013)
Cultural facility (per 10)	1.011**	(0.004)	1.008*	(0.003)	1.007*	(0.003)
Sports and leisure facility	1.027***	(0.005)	1.025***	(0.004)	1.025***	(0.004)
AIC	92,043		85,973		85,308	
Pseudo R^2	0.265		0.313		0.318	

Note: 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 6-hour time periods, the variables *previous crime location on the same daypart with a greater than 6-hour difference* and *previous crime location on different daypart with a 0-hour difference* do not yield any scores and are therefore left out of the analysis.

$*p < 0.05$, $**p < 0.01$, $***p < 0.001$ (two-tailed).

4.4.2 Timing of crime within the day

In Model 2 of Table 4.2, we observe that the effects of all hour-difference variables were positive and statistically significant. The size of the ORs 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 *3- to 5-hour difference*. A joint test showed that the effects of the consecutive pairs of all three hour-difference variables (i.e., 0-hour difference versus 1- to 2-hour difference and 1- to 2-hour difference versus 3- to 5-hour difference) differed statistically significantly, ($\chi^2(2) = 166.87$, $p < 0.001$). 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 ORs, ($\chi^2(2) = 38.37$, $p < 0.001$). 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 6-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.

4.4.3 Combined model: timing of crime within the week and day

Model 3 (Table 4.3) 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., 0-hour difference versus 1- to 2-hour difference, 1- to 2-hour difference versus 3- to 5-hour difference, and 3- to 5-hour difference versus greater than 6-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 0-hour difference* than when the offender had not committed a crime in that area before. The ORs decreased to 3.22 when both crimes were committed on the *same weekend day with a greater than 6-hour difference*. The ORs of the consecutive pairs of hour-difference variables differed statistically significantly ($\chi^2(3) = 87.46$, $p < 0.001$).

A similar but somewhat smaller decreasing pattern was found when both offenses were committed during the *same day of the week* ($\chi^2(3) = 92.61$, $p < 0.001$). We still observe a decay in effect sizes for crimes committed on a *different weekend day* ($\chi^2(3) = 9.30$, $p = 0.026$), *different day of the workweek* ($\chi^2(3) = 39.20$, $p < 0.001$), and *different part of the week* ($\chi^2(3) =$

26.41, $p < 0.001$). However, the ORs are expectedly smaller compared to those within the same part of the weekend or week. The joint test showed that the ORs of the consecutive pairs of the hour-difference variables differed statistically significantly between all the five week categories ($\chi^2(15) = 329.13$, $p < 0.001$). An additional joint test, ($\chi^2(4) = 2018.42$, $p < 0.001$), showed that the ORs for the most similar time categories (i.e., on the exact same weekend or weekday with a 0-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 6-hour difference between the offenses). We can thus conclude that Hypothesis 1c is also supported.

4.4.5 Combined model for same versus different types of crime

Model 4 (Table 4.3) 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 ORs 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* ($\chi^2(20) = 135.63$, $p < 0.001$). 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.

4.4.5 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 4.2 and 4.3) show a pseudo R^2 of 0.32. This is a substantial increase compared to the pseudo R^2 of 0.26 of the baseline model (Model 0, Table 4.2) 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 0.2 and 0.4 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 Measurements section). The results (not shown here) confirm the overall conclusions with regard to our hypotheses.

Table 4.3 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 (N = 1,787,105 offense-alternatives for 12,639 repeat offenses, committed by 3,666 offenders).

Variable	**Model 3** Timing within the week & day (H1c)		**Model 4** Timing within the week & day by crime type (H2) Same crime type		Different crime type	
	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- to 2-hour difference	7.826***	(1.043)	10.785***	(2.027)	3.624***	(0.719)
3- to 5-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- to 2-hour difference	3.466***	(0.558)	3.856***	(0.970)	2.545***	(0.574)
3- to 5-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- to 2-hour difference	4.638***	(0.497)	6.113***	(0.842)	2.593***	(0.461)
3- to 5-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)
Different weekday with						
0-hour difference	5.965***	(0.615)	6.988***	(0.963)	2.442***	(0.462)
1- to 2-hour difference	4.458***	(0.299)	4.323***	(0.399)	2.570***	(0.249)
3- to 5-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- to 2-hour difference	3.375***	(0.237)	3.200***	(0.341)	2.563***	(0.231)
3- to 5-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)	
Distance from current residential area	0.731***	(0.005)		0.728***	(0.005)	
Proportion non-Western residents	2.344***	(0.164)		2.381***	(0.169)	
Proportion single-person households	1.898***	(0.243)		1.864***	(0.239)	
Population density (per 1,000)	0.993**	(0.002)		0.993**	(0.002)	
Number of employees (per 1,000)	1.026***	(0.003)		1.027***	(0.003)	
Retail business (per 10)	1.034***	(0.004)		1.034***	(0.004)	
Hotels, restaurants and bars (per 10)	1.019*	(0.008)		1.019*	(0.008)	
Schools (per 10)	1.050*	(0.024)		1.053*	(0.024)	
Health-care facility (per 10)	0.974*	(0.013)		0.972*	(0.012)	
Cultural facility (per 10)	1.008*	(0.003)		1.009**	(0.003)	
Sports and leisure facility	1.025***	(0.004)		1.026***	(0.004)	
AIC	85,394			85,477		
Pseudo R^2	0.319			0.318		

Note: OR = odds ratio coefficient; SE = standard error corrected for clustering within offenders; AIC = Akaike information criterion.

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$ (two-tailed).

4.5 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 0- to 2-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 spatio-temporal 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 & Malleson, 2015; Johnson et al., 2012) and day (e.g., Haberman & Ratcliffe, 2015; Sagovsky & 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 cyclical 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 et al., 2004; Mohler et al., 2015; Rummens et al., 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 cyclical time effects into account but merely rely on spatial and temporal decay functions. Although Johnson et al. (2007b) already developed a predictive approach that takes cyclical 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 cyclical time patterns in crime location choice. This stresses the importance for future predictive policing methods to combine spatio-temporal decay functions and cyclical 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' spatio-temporal 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 et al., 2010). These studies found little evidence that solved and unsolved offenses display large spatio-temporal differences.

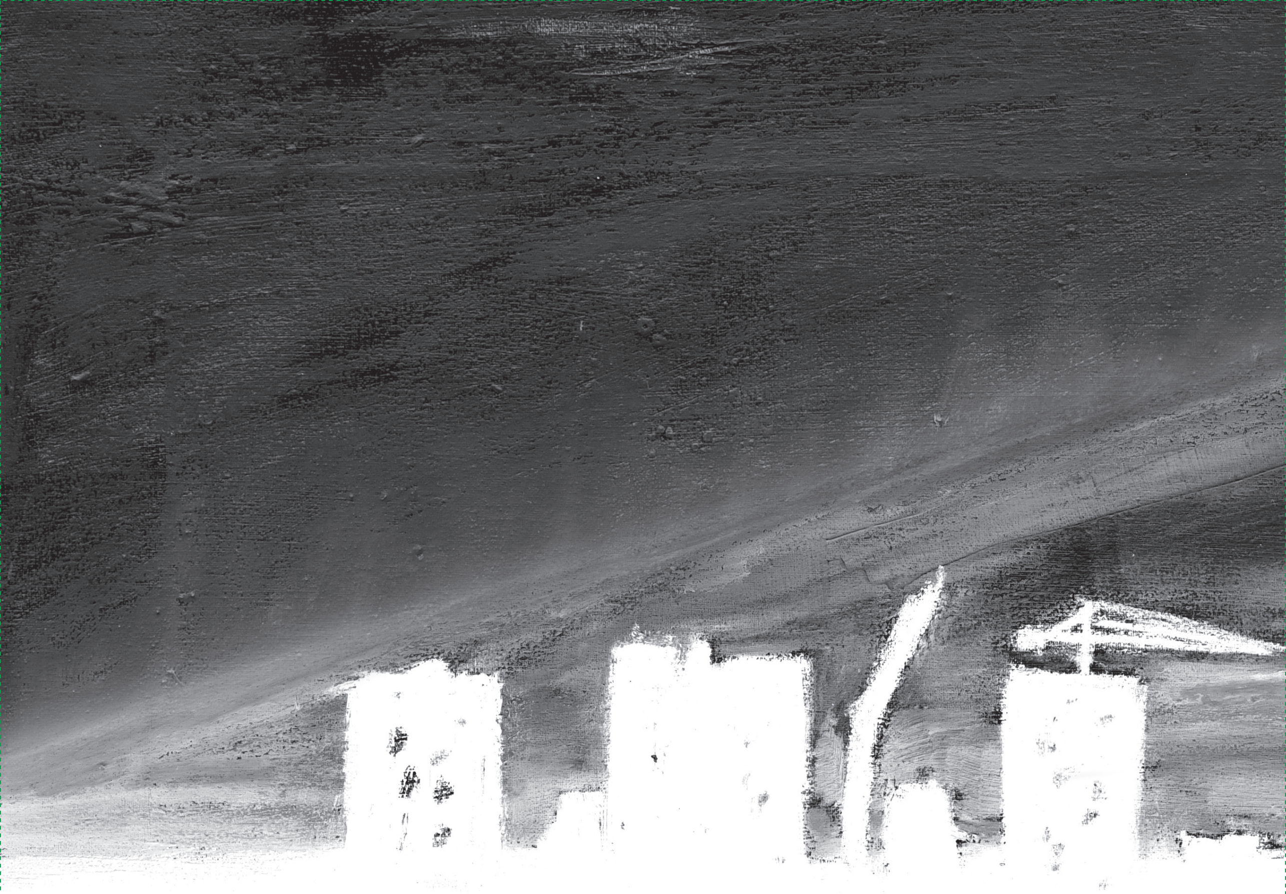
Nevertheless, the fact that our offender population was arrested for offenses committed at a certain place and time might seem contradicting to our predictions based on rational choice and crime pattern theory. From a purely rational choice perspective, one would expect that offenders adjust their cost-benefit 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 & 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 spatio-temporal 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 spatio-temporal 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 & 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 cyclical 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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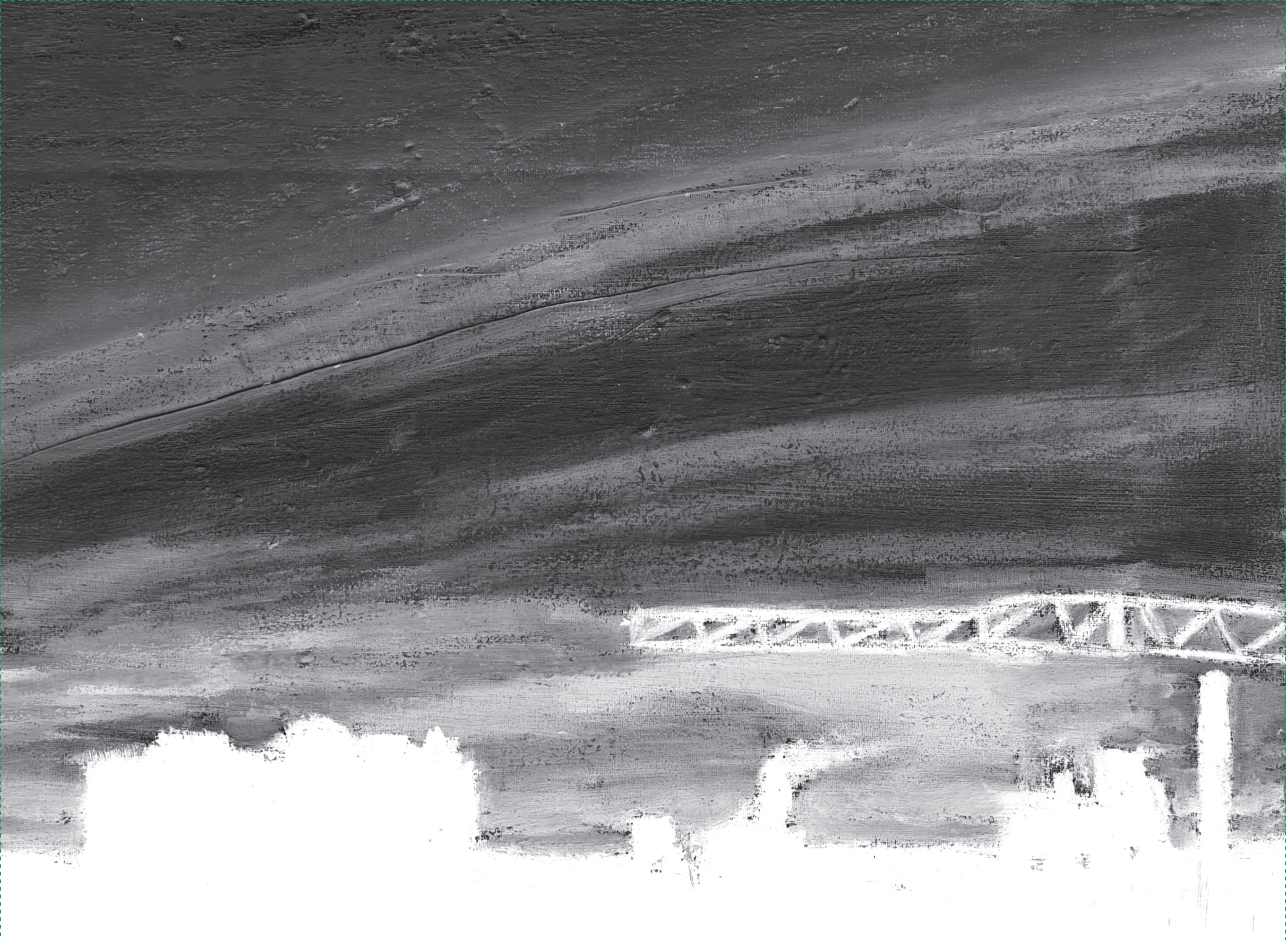

CHAPTER 5

Right place, right time? Making crime pattern theory time-specific

Abstract

Objectives. Crime pattern theory and the related empirical research have remained rather a-temporal, as if the timing of routine activities and crime plays no role. Building on previous geography of crime research, we extend crime pattern theory and propose that an offender's spatial knowledge acquired during daily routine activities is not equally applicable to all times of day.

Methods. We put this extended theory to a first empirical test by applying a discrete spatial choice model to detailed information from the Netherlands on 71 offenses committed by 30 offenders collected through a unique online survey instrument. The offenders reported on their most important activity nodes and offense locations over the past year, as well as the specific times they regularly visited these locations.

Results. The results show that almost 40% of the offenses are committed within the neighborhoods of offenders' activity nodes, increasing to 85% when including first-, second- and third-order neighborhoods. Though not statistically significant in our small sample, the results further suggest that offenders are more likely to commit crime in neighborhoods they have regularly visited at the same time of day than in neighborhoods they have regularly visited at different times of day.

Conclusion. Our extension of crime pattern theory is only tentatively supported. We argue for replication research with larger samples before any firm conclusions are warranted.[19]

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5.1 Introduction

5.1.1 Background

Why do crimes occur both where and when they do? Environmental criminologists have been studying these questions for decades (Wortley & Townsley, 2017). Much research has focused on the spatial clustering of crime (e.g., Chainey & Ratcliffe, 2013; Eck et al., 2005; Sherman et al., 1989), on patterns of (near) repeat victimization (e.g., Bowers & Johnson, 2005; Farrell et al., 1995; Morgan, 2001) and on seasonal variations in crime (e.g., Andresen & Malleson, 2013; Ceccato, 2005; Linning et al., 2017). Since the 1970s, a number of key environmental criminological theories have been developed for understanding why such spatio-temporal crime patterns exist. Instead of individuals' motivations to engage in crime, these theories start from the spatio-temporal organization of people's activities and opportunities for crime. Cohen and Felson (1979) defined the crime event as the convergence in space and time of a motivated offender with a suitable target in the absence of capable guardians.

Where such convergences are most likely to occur is best understood using the geometry of crime in crime pattern theory (Brantingham et al., 2017; Brantingham & Brantingham, 1981; 1993). According to this theory, everyone—including offenders—develops an individual awareness space that consists of their major routine *activity nodes* such as home, school, workplaces, and leisure activity locations (i.e. their activity space), the travel paths that connect them and everything within the visual range of the offender. When visiting these activity nodes, offenders acquire knowledge of their spatial environment (Brantingham & Brantingham, 1981). As depicted in Figure 5.1, the theory posits that offenders are most likely to commit crime (the red stars) at those locations where their individual awareness space (in white) intersects with the spatial distribution of suitable targets (the dark ellipses). 5

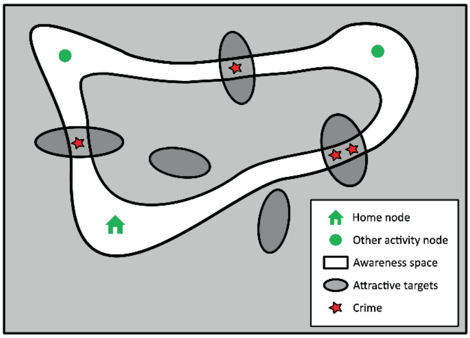


Figure 5.1 Predicted crime locations according to crime pattern theory, adapted from Brantingham and Brantingham (1981, p. 42).

Over the past decades, a considerable body of knowledge has been developed about the locations where offenders tend to commit crime (for a comprehensive literature on crime location choice, see Ruiter, 2017). Research showed that offenders commit crimes near their current and former residential homes (e.g., Baudains, Braithwaite & Johnson, 2013; Bernasco & Kooistra, 2010; Johnson & Summers, 2015), as well as those of close family members (e.g., Menting, 2018; Rossmo, Lutermann, Stevenson & Le Comber, 2014) and friends (e.g., Wiles & Costello, 2000). Offenders are also likely to return to previously targeted areas (e.g., Bernasco et al., 2015; Van Sleeuwen et al., 2018; Chapter 4) and they commit offenses close to other routine activity nodes such as their schools, workplaces and locations for leisure activity (Menting et al., 2020).

Although the core of crime pattern theory explains spatial patterns in crime, it also addresses *temporal* crime patterns by acknowledging that target attractiveness can be time-varying. A place might be attractive for crime during the day but unattractive at night. For example, homes are often occupied in the evening and night but vacant during office hours, whereas this pattern is reversed for most businesses and facilities. Figure 5.2 depicts this by decomposing the locations of targets from Figure 5.1 into time-varying target attractiveness, showing that the same place can be attractive for an offender during the day but not so much during the night. Hence, offenders are only expected to commit crime at those places when targets are attractive.[20] Brantingham et al. (2017) recently provided an example of this when they stated that "the argument for complete randomness of targets and victims is no longer plausible" (p. 98).

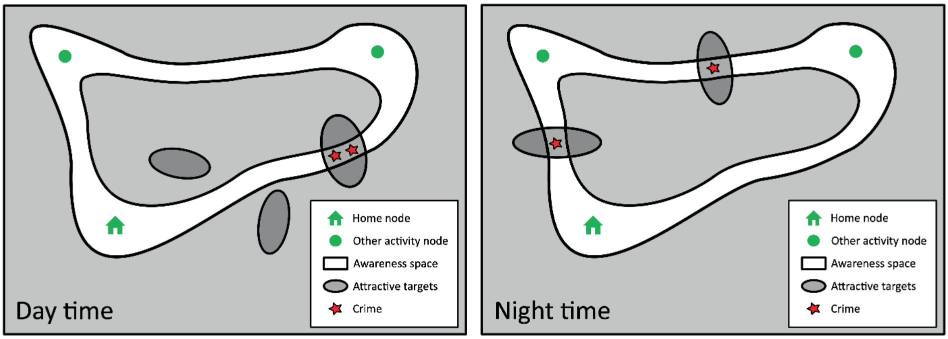


Figure 5.2 Attractive targets are present at different locations during the day (left) and during the night (right), impacting the predicted crime locations at different times of day.

[20] For clarity reasons, we only show the presence or absence of attractive targets (the grey circles). In reality, target attractiveness might vary more gradually over time.

5.1.2 The present study

We argue that Figure 5.2 only tells half of the story. Building on previous geography of crime research, the aim of this article is twofold. First, expanding upon previous theoretical arguments made by others (see e.g., Curtis-Ham et al., 2020; Johnson et al., 2007b; Van Sleeuwen et al., 2018; Chapter 4), we argue how crime pattern theory needs to be extended to better understand both where *and* when crimes are committed. Specifically, we argue that the theory needs to include time-varying applicability of spatial knowledge. Although time-varying target attractiveness is acknowledged (see Figure 5.2), crime pattern theory has so far ignored that specific knowledge of one's spatial environment acquired during daily routines might only be *applicable* to specific times. All tests of the theory thus far have implicitly assumed a-temporal and time-stable awareness spaces, which suggests that offenders would be equally aware of criminal opportunities at different times of the day irrespective of when they actually visit the places during their routine activities. From this assumption follows that offenders would commit offenses in all possible places within their awareness spaces at any time and day. We question this assumption and posit that the spatial knowledge offenders acquire during their daily routine activities is often only applicable at certain times of day (also see Van Sleeuwen et al., 2018; Chapter 4).

Van Sleeuwen et al. (2018; Chapter 4) already argued that repeat offenders would especially return to previously targeted areas at the same time of day, while Johnson et al. (2007b) applied the idea of similarity in time of day to the specific case of (near) repeat burglary events. In the present study, we generalize these claims to all offenders and other activity nodes by reconceptualizing the concept of awareness space itself. Awareness spaces clearly comprise all kind of activity nodes; not only prior crime locations. And although Curtis-Ham et al. (2020) mention the similarity of prior activity timing as one of the 'relevance' factors in their theoretical framework for estimating crime location choice based on awareness space, they do not specify the underlying mechanism regarding the temporal *applicability* of spatial knowledge. Our first contribution is thus theoretical: the applicability of the spatial knowledge offenders acquire during their daily routine activities needs to be conceptualized as time-varying in crime pattern theory. We argue for this extension of the theory in order to provide a better explanation for why crimes are committed not only in certain places, but also at certain times.

Second, as a first empirical test of our extended theory, we designed an online survey in which we examined the time-specificity of offender activity spaces in more detail. Most empirical research on crime patterns uses police data, which generally contain very limited information on the activity spaces of offenders. Often only the home and offense location are known (Ruiter, 2017). In addition, the one study that investigated other activity nodes such as schools, workplaces and leisure activities (Menting et al., 2020), did not measure at what times of day these places were visited nor the timing of the offenses. Lastly, the few ethnographic studies that investigated temporal crime patterns in relation to a variety of different activity nodes were all based on qualitative research designs that did not systematically record an extensive set of routine activity nodes for all offenders that were interviewed (e.g., Cromwell et al., 1991; Rengert & Wasilchick, 2000). In the present study, we measured not only the offenders' most important activity nodes and offense locations in the previous year, but also recorded the specific times they regularly visited these activity nodes. This allows for a first test of hypotheses derived from our extended crime pattern theory about time-varying applicability of spatial knowledge using discrete spatial choice models.

5.1.3 Extending crime pattern theory with time-varying applicability of spatial knowledge

Crime pattern theory acknowledges that some characteristics of places that affect their crime attractiveness are time-varying (e.g., home occupancy in residential neighborhoods, or the number of cars parked on a parking lot), while other features are relatively time-stable (e.g., the presence of locks and escape routes). As offenders go about their daily routines, they acquire important information about both these time-varying and time-stable features surrounding their routinely visited locations. This information will then be used in their criminal decision-making (see Figure 5.2).

However, crime pattern theory has not been explicit about the degree in which offenders' acquired knowledge of their (partly time-varying and partly time-stable) spatial environment is actually *applicable* at different times (also see Van Sleeuwen et al., 2018; Chapter 4). By definition, the acquired knowledge of time-constant characteristics will apply regardless of the specific time. But the same cannot be said of time-varying characteristics: knowledge of time-varying features might only apply to specific times of day (i.e., the same times of day at which this knowledge was acquired). Of course, using simple heuristics, part of the knowledge that relates to time-varying features might also be generalizable to other times of day, and the offender may act accordingly. Even if offenders might have specific routine activity nodes they exclusively visit during the day, such as workplaces or shopping malls, they could still make good estimations about what the situation would be like at night. For example, based on the regular opening and closing hours of supermarkets, offenders who only visit those places during daytime shopping can still make reasonably good inferences about not many people being at that location after 9 p.m. because the shop is then closed.

Nevertheless, the knowledge that people gain about a certain area at a certain time of day by directly observing it during their routine visits, is more accurate and therefore better applicable to what the situation would look like around that time of day than a generalization based on heuristics. For example, the area around the supermarket might actually be quite busy after 9 p.m. for a completely different reason. Hence, the acquired knowledge of a certain activity node will be more applicable when the node was previously visited at a similar time. Let's revisit the crime pattern theory diagrams and imagine that it shows the awareness space of an offender who regularly visits three activity nodes: his home, his work location, and his favorite bar in a drinking area. As the offender only visits the drinking area late at night, he develops spatial awareness that mainly applies to the nighttime setting and it is unrealistic to assume that the knowledge about the area is equally applicable to the daytime setting. At night, his spatial knowledge thus best applies to the area where the bar is located. In the daytime, the offender is expected to have more accurate knowledge about suitable targets in the area he usually visits during office hours, because he works there. At both times, the offender will be aware of what the situation is like in his home area. As depicted in Figure 5.3, we thus argue for time-varying applicability of spatial knowledge: the awareness space itself differs between daytime and nighttime, and not only the locations of attractive targets as per Figure 5.2.

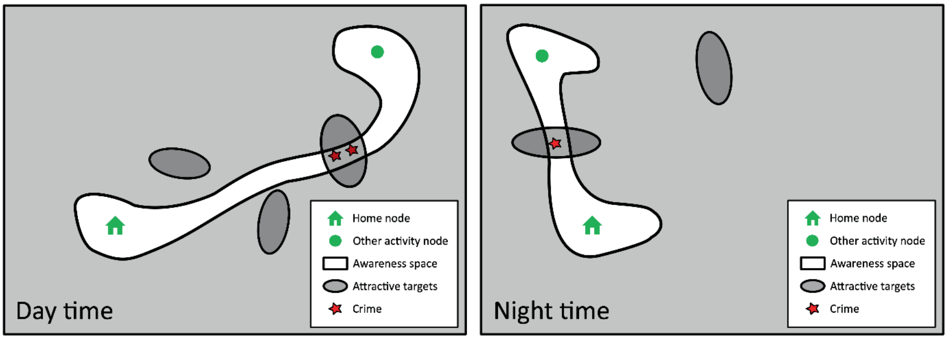


Figure 5.3 Extended crime pattern theory, illustrating the applicability of spatial knowledge during the day (left) and during the night (right).

Although Van Sleeuwen et al. (2018; Chapter 4) also argued for time-specific applicability of spatial knowledge, our argument expands upon theirs. Van Sleeuwen et al. argued that offenders develop time-specific knowledge of *crime locations* and offenders would therefore commit their *repeat* offenses in the same areas at similar times as the prior offenses. In the present paper, we generalize this idea and reconceptualize the awareness space concept itself. We posit that the applicability of spatial knowledge about the entire awareness space is time-specific, not only for previous crime locations. This implies that awareness spaces are not merely spatial, as suggested by Figure 5.1, but in fact temporally varying due to the fact that people visit routine activity nodes at certain times of day and thus acquire spatial knowledge that is best reflective of those times. This implies that knowledge of suitable targets in certain areas would also be most applicable at the times of day these areas were visited.

Of course, offenders also acquire knowledge about time-stable features of the environment and for many time-varying features often simple heuristics suffice. For example, by knowing the opening hours of businesses and facilities one can generally estimate reasonably well when certain areas will be crowded with people and when they go quiet. For this reason, we expect that even though the offender's knowledge about the crime attractiveness of an area he only visits during the day might be less applicable to that area at night (or vice versa), his knowledge about that particular area is still somewhat applicable to that area. The offender thus has some knowledge of the area, certainly more than that of any other area he does not routinely visit. Routinely visiting an area at a specific time of day will thus provide spatial knowledge about the area that is best applicable to situations at that specific time, and less—but still somewhat—predictive for situations at different times. Based on our extension of crime pattern theory to understand both the spatial and temporal patterns in crime, we derive a first set of testable hypotheses about where offenders are expected to commit offenses at specific times of day:

> ***Hypothesis 1***: Offenders are more likely to commit crime in areas they have regularly visited at the same time of day than in areas they have regularly visited at different times of day.
>
> ***Hypothesis 2***: Offenders are more likely to commit crime in areas they have regularly visited at different times of day than in areas that are outside their activity space.

5.2 Data and methods

In order to examine the time-varying applicability of spatial knowledge in more detail and test our hypotheses, we designed the Time-specific Activity Space (TAS) survey. In this online survey, a sample of offenders reported extensively on the locations of the most important activity nodes they had regularly visited the year prior to the survey and at what times of day and days of week they had visited these nodes, as well as where and when they had committed offenses. In the remainder of this section, we discuss the design of the study and the sampling procedure, the contents of the questionnaire, and how we operationalized our measures as well as the method used for testing our hypotheses.

5.2.1 Study design and sampling procedure

After obtaining permission of the Ministry of Justice and Security and Dutch National Police for our study design and a positive advice from the Ethics Committee for Legal and Criminological Research of the Vrije Universiteit Amsterdam, data on suspects from the Dutch police regions The Hague and North-Holland for the year 2017 were obtained. Although information about the final conviction rate for this specific group was not available in the police data, in general, more than 90% of police suspects are found guilty at a later stage (Blom et al., 2005). For inclusion in our sample, a suspect needed to (1) have at least one recorded offense in 2017 that was filed to the public prosecutor, (2) be 18 years or older at the time of the sample selection, and (3) have a valid home address in the Netherlands for sending the invitation letter. Due to a stricter interpretation of the Dutch police data law, the original suspect dataset obtained from the police only included relatively minor offenses that the police did not need a 72-hour investigation for (such as vehicle theft and shoplifting). Therefore, only offenders with less serious offenses and shorter offense histories were available for possible inclusion in our study. Of the 4,102 suspects that met criteria (1) and (2), 3,786 (92.3%) could be matched with Dutch information system on residential addresses (Basis Registratie Personen; BRP) to obtain a valid home address.

Following the same study design as used by Menting et al. (2020), respondents were approached by sending them an initial invitation letter, which contained a link to our project's website and a unique login token for accessing the online survey. All non-respondents were sent a reminder letter after 1.5 weeks. At the beginning of the survey, respondents were presented a detailed information page about the research project, the contents of the questionnaire and a privacy statement.[21] The survey could only be started after digitally signing the informed consent form. After completing the full survey, respondents were sent a gift card of 25 euro. The invitation letters were sent in several batches from May to July 2019. When the survey was taken offline at the end of August 2019, a total of 501 respondents had started with the survey (42 letters were returned as undeliverable; response rate 13.4%)[22] and reported about 1990 different activity nodes. 363 respondents had fully completed the survey, of which 30 respondents reported having committed at least 1 crime in the year prior to the survey.[23] In total, they reported on 71 unique crimes.

5.2.2 Time-specific Activity Space (TAS) survey

The survey first asked to report on daily and weekly routine activities, categorized in seven different domains: (1) residences, (2) schools, (3) jobs, (4) sports activities, (5) shopping, (6) going out, and (7) any other activities, for which respondents could specify the type of activity themselves. For each domain, the respondents were asked to indicate whether they had visited such an activity node about weekly over the past year. If so, they were asked for a maximum of six locations per domain to pinpoint the exact location using the Google Maps functionality included in the LimeSurvey platform to which we added an interactive search bar: three for current activity locations and three for past activity locations (except for residences, as only one current home location could be reported and up to a maximum of five prior home locations in the past year). The pinpointed locations were automatically geocoded by storing the longitude-latitude information.

For each of these locations, respondents indicated during which days of the week and times of the day they had usually visited that location in the past year. For each day, we presented the respondents with eight possible time slots of three hours each (starting from midnight-3 a.m. and ending at 9 p.m.-midnight). Respondents were also asked during which months of the previous year they had regularly visited that location.

[21] We explicitly stated that all the given answers of the respondents would be carefully stored on a secure server that only employees of the study could access and that we would never share the completed answers with any other party. In this way, our aim was to encourage respondents to report about any crime in the past year, both known and unknown to the police.

[22] Response rate as of September 2020. This response rate is comparable to the 12.4% response in the study of Menting et al. (2020) and the 18.3% response in the nationwide online transportation survey of Statistics Netherlands (Statistics Netherlands, 2016).

[23] The offenders were selected in 2017 but asked about their offending in 2018-2019 (i.e. the year prior to the survey date). This lag was due to time delays in accessing police data and because we did not want to miss out on potential imprisoned respondents.

In the second part of the survey, we asked respondents whether they had committed the following crime types in the past year: (1) residential burglary, (2) theft of/from a bicycle, car or other (motor) vehicle, (3) theft from a shop/shoplifting, (4) theft (of an object) from a person, (5) robbery, (6) assault, and (7) vandalism. For up to three incidents per crime type, we asked respondents to provide spatio-temporal details, similar to the spatial and temporal survey questions regarding their routine activities: the exact location on an interactive map of the Netherlands, and in which month of the year, day of the week and 3-hour time slot the crimes were committed.

For each of the seven activity domains as well as for each reported crime type, respondents were asked to indicate the accuracy of their responses for the locations (i.e., whether their selection indicates a specific address, street, neighborhood, or city), as well as the accuracy of the reported time slots of the day, days of the week and months of the year (i.e., very accurate, reasonably accurate, reasonably inaccurate, very inaccurate).

5.2.3 Operationalization and method

In order to determine the adequate spatial and temporal resolution for our unit of analysis, we first checked the reported level of accuracy for the seven routine activity domains and the five different reported types of crime. Spatial accuracy was generally higher for the reported routine activity nodes than for the crimes. However, for all 12 categories combined, more than three-quarters of the locations were indicated to be reported at least at the neighborhood level. Therefore, we geocoded the longitude-latitude information to one of the 13,305 unique neighborhoods in the Netherlands for the year 2018, with a median area of 0.66 km^2 (mean = 2.63, range = 0.02-130.14) (Statistics Netherlands, 2019). To ensure that activity patterns preceded the crimes, we removed those activity nodes respondents only started visiting after the crime event. For more than 80% of the reported times in the survey, the respondents indicated the timing of their routine and criminal activities in the eight different 3-hour time slots as “reasonably accurate” or “very accurate”. The data show that our 3-hour time slots offered respondents a more detailed temporal granularity than necessary: most locations are visited across a number of 3-hour time slots. We therefore divided the time of day category into the two most distinct time blocks: daytime (6 a.m.-6 p.m.) versus nighttime (6 p.m.-6 a.m.).[24]

[24] Although the theoretical arguments made about differences between daytime and nighttime activity spaces (see paragraph 5.1.3) could also be applied to weekdays versus weekends, we were not able to empirically test this hypothesis because there was too much overlap between the activities that took place on both weekdays and weekends (i.e. many locations were visited during both).

The dependent variable *crime committed in neighborhood* (1 = yes; 0 = no) indicates whether or not an offense was committed in a specific neighborhood. For each of the 71 crimes, the neighborhood in which the offender had committed the offense was assigned a score of 1, while all other 13,304 neighborhoods were scored 0. The independent variable *neighborhood routinely visited* (1 = yes; 0 = no) indicates whether or not a neighborhood was part of the offenders' activity space in the period before or during the crime event. A score of 1 was assigned to all the neighborhoods the offender routinely visited and all other neighborhoods were scored 0. In order to test our hypotheses, we combined the neighborhood and timing information into two independent variables: *neighborhood routinely visited at same time of day as crime event* (1 = yes; 0 = no) and *neighborhood routinely visited at different time of day as crime event* (1 = yes; 0 = no). For example, when a certain neighborhood was routinely visited by an offender during the night (i.e., inside the nighttime activity space of the offender) and the crime was committed during the day (or vice versa), the former variable scored 0 and the latter scored 1. When a crime was committed during the day in a neighborhood that was also part of the offender's daytime activity space (or both during the night), or when crime was committed in a neighborhood that was both part of the offender's daytime and nighttime activity space, the former variable scored 1 and the latter 0.[25]

To provide a first empirical test of our extended crime pattern theory, we estimated a conditional logit model as commonly applied in crime location choice research (Bernasco & Ruiter, 2014; Ruiter, 2017). The choice outcome is the neighborhood the offender selected for committing the offense. Because each of the 71 offenses could have been committed in any of the 13,305 neighborhoods of the Netherlands in 2018, the final dataset for analysis is a data matrix of 944,655 rows (containing 13,305 neighborhood rows for each of the 71 crimes to be explained). Because the small sample size does not justify using normal standard errors, we calculated bootstrapped standard errors based on 100 samples. These were also cluster-corrected, because the 71 offenses had been committed by 30 different offenders. The results of the conditional logit models are presented using odds ratios (ORs) and their respective bootstrapped cluster-corrected standard errors (SEs). As the independent variables score 0 when the offender had not routinely visited a certain neighborhood before and therefore that neighborhood is outside the activity space of the offender (i.e., the reference category), the effects of the study variables are expected to be positive with odds ratios greater than 1.

[25] We also estimated a conditional logit model with three independent variables that also includes the variable neighborhood routinely visited at both same and different time of day as crime event (see Table 5.3 in the Appendix), but the overall conclusions with regard to our hypotheses remained the same.

5.3 Results

5.3.1 Descriptive statistics

We start this section with descriptive statistics of the offenders and their offenses. Half (i.e. 15) of the 30 offenders reported having committed only a single offense in the year prior to the survey. Three offenders had committed two offenses, nine offenders three offenses, and the remaining three offenders had committed 4, 8, and 11 offenses, respectively. Regarding the specific type of offenses, the following frequencies were observed for the 71 offenses in the dataset: two residential burglaries, nine thefts of/from a bicycle, car or other (motor) vehicle, 40 thefts from a shop/shoplifting, 14 assaults, and six acts of vandalism.

To investigate the extent to which offenders committed their offenses inside their activity spaces, Table 5.1 presents a cross-tabulation of activity space by crime location (N = 71 crimes * 13,305 possible neighborhoods = 944,655). For each offense, there were several possibilities in each of the 13,305 Dutch neighborhoods: a crime was either committed or not committed in that neighborhood, and the neighborhood was either inside or outside the activity space of the offender. Although the offenders could have committed their crimes in all of the 13,305 possible neighborhoods of the Netherlands, we observe that 28 out of the 71 crimes were committed in a neighborhood that the offender routinely visited in the period before or during the crime event (median area = 0.36 km^2). This means that 39.4% of the offenses are committed within the neighborhoods of offenders' own activity nodes.

Table 5.1 Cross-tabulation of activity space by crime location (N = 71 crimes * 13,305 possible neighborhoods = 944,655).

Variable	No crime	Crime	Total
Neighborhood is ...			
... Outside of offender's activity space	944,332	43	944,375
... Inside of offender's activity space	252	28	280
Total	944,584	71	944,655

We not only expect that neighborhoods with routine activity nodes have a higher chance to be targeted, but also—to a lesser extent—neighborhoods nearby, which offenders might visit less frequently or only traverse on their way to their activity nodes. If we include first-order spatial lags (i.e., neighborhoods adjacent to those with the activity nodes), second-order spatial lags, and even third-order spatial lags, the median area of the neighborhoods increased to 3.37 km^2, 14.5 km^2, and 55.6 km^2, respectively. We indeed find that the percentage of offenses that were committed inside offenders' activity spaces rapidly increases from 59.2% (first-order spatial lags) to 70.4% (second-order lags), and 84.5% (third-order lags).

5.3.2 A first test of the extended theory

The results of the conditional logit model that tests whether offenders are more likely to commit crime in neighborhoods they have regularly visited at the same time of day than in neighborhoods they have regularly visited at different parts of the day are displayed in Table 5.2.[26] The results show that the odds ratio for our main study variable *neighborhood routinely visited at same time of day as crime event* is positive and statistically significant ($p < 0.001$). This means that offenders are more likely to commit crime in neighborhoods that were part of their time-specific activity space compared to neighborhoods that were not. More specifically, the odds of committing crime in neighborhoods that are routinely visited at the same time of day as the crime event is more than 2,500 times that of committing crime in neighborhoods not part of one's activity space. Moreover, we observe that this odds ratio (OR = 2589.71) is estimated to be considerably higher than the odds ratio for *neighborhood routinely visited at different time of day as crime event* (OR = 1209.00). A Wald Chi-Squared difference test on our small sample does not detect a statistically significant difference between the two odds ratios ($\chi^2(1) = 0.01$, $p = 0.915$), but the difference is clearly in the expected direction. The odds ratio for *neighborhood routinely visited at different time of day as crime event* also does not reach statistical significance ($p = 0.324$).

Table 5.2 Conditional logit model testing the effects of time-varying activity spaces on crime location choice (N = 71 crimes * 13,305 possible neighborhoods = 944,655).

Variable	OR	SE	Z	P
Neighborhood routinely visited at ...				
... Same time of day as crime event	2589.71	1365.30	14.91	0.001
... Different time of day as crime event	1209.00	8703.08	0.99	0.324
Pseudo-R^2	0.27			

Note: OR = odds ratio coefficient; SE = bootstrapped cluster-corrected standard error.

[26] The conditional logit model uses the original neighborhood areas instead of the lagged neighborhoods.

With only our two independent study variables, the pseudo-R^2 of the model is 0.27, which represents according to McFadden's guidance an excellent fit to the data (McFadden, 1978; p. 307). The results suggest that offenders are more likely to commit crime in neighborhoods they have regularly visited at the same time of day than in neighborhoods they have regularly visited at different times of day, although the effect size difference was not statistically significant in our small sample—but clearly in the expected direction. This provides only tentative support for Hypothesis 1. In addition, offenders also appear to be more likely to commit crime in neighborhoods they have regularly visited at different times of day than in neighborhoods that are outside their activity space, but the odds ratio was not statistically significant. This also provides only tentative support for Hypothesis 2.

5.4 Discussion

According to crime pattern theory, offenders commit crime at those places where their individual awareness spaces overlap with the spatial distribution of attractive targets. However, both the theory and the related empirical research have remained rather a-temporal, as if the timing of routine activities and crime plays no role. In the present study, we extended crime pattern theory and proposed that an offender's spatial knowledge acquired during daily routine activities is not equally applicable to all times of day. For a first empirical test of the extended theory, we collected detailed information about the spatio-temporal routine activity patterns and crime locations in a high-risk offender sample. The results showed that almost 40% of the offenses (39.4%) were committed within the neighborhoods of offenders' activity nodes, increasing to 84.5% when including first-, second- and third-order spatial lags surrounding the activity node neighborhoods. This corresponds with findings from the study of Menting et al. (2020), who reported 39.3% and 88.6%, respectively. This finding provides strong support for the original crime pattern theory (Brantingham et al., 2017; Brantingham & Brantingham, 1981; 1993). Though not statistically significant, the results further suggest that offenders are more likely to commit crime in neighborhoods they have regularly visited at the same time of day than in neighborhoods they have regularly visited at different times of day. Our extension of crime pattern theory is therefore only tentatively supported.

Although this first empirical test provides some evidence for our extended theory, it is important to emphasize that our conclusions are tentative as the size of our sample of offenses was quite small (*N* = 71 offenses committed by 30 offenders). Also, a non-experimental research design obviously cannot fully rule out possible selection bias. As our respondents were sampled from police register data on suspected offenders from two specific police regions in the western part of the Netherlands (The Hague and Noord-Holland), we might not be able to generalize our findings to the broader offender population; to offenders in other parts of the country or to offenders that escaped arrest. The findings we observe might in part be related to the police being better able to solve offenses that were committed inside the offenders' activity spaces. However, research using DNA-traces found at crime scenes suggests that the spatial patterns of solved and unsolved cases do not differ much (Lammers, 2014).

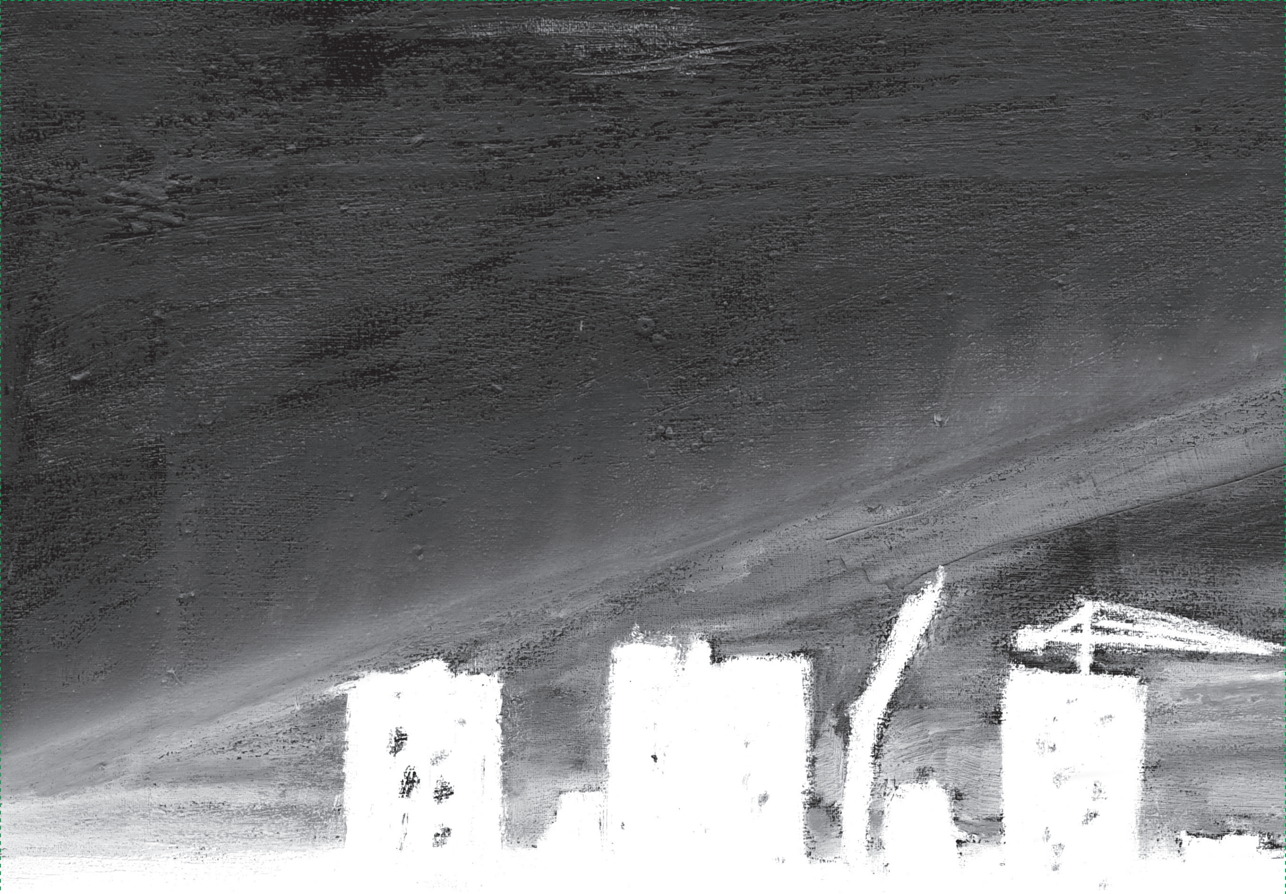
As explained in more detail in paragraph 5.2.1, the original suspect data from the police included relatively minor offenses from offenders with relatively short offense histories. Compared to offenders with longer offense histories and more serious offenses, this suspect group is found to have a decreased likelihood of continuing to commit crime in subsequent years (Lammers et al., 2012). We find some confirmation for this finding when we compare the percentage of respondents that reported undertaking a crime in our study (8.3%) with the percentage found in the study of Menting et al. (2020) (18.9%). Menting and colleagues used exactly the same research design, but a sample that was not restricted to suspects of minor crimes only. If the findings of our study would be related to the number and severity of offenses, we should have found different spatial results than those presented by Menting et al. (2020), who analyzed a sample that also included more persistent offenders who committed more severe offenses. However, the results were actually quite comparable between the two studies.

Another common limitation of retrospective survey research is that the accuracy of recall from respondents' memory is uncertain. This would not be a problem if all respondents have equal memory loss, but respondents who had committed their crimes outside of their awareness space might have had more difficulty recollecting details about the crime locations and timings than respondents who had committed crime within their awareness space. However, we analyzed crime locations at the neighborhood level and dichotomized the timing of crime into daytime and nighttime crimes, which makes possible inaccuracy of recall less problematic. Besides, the respondents indicated that over three-quarters of the locations were reported at neighborhood level or with higher accuracy, and in more than 80% of the reported times, the timing of their activities was reported reasonably or very accurately.

Notwithstanding these shortcomings, this study has presented an extended crime pattern theory to better explain not just where but also when crimes are committed. We argued that the applicability of the spatial knowledge offenders acquire during their daily routine activities needs to be conceptualized as time-varying, because it may not be applicable to all times of day. Although we presented the first tentative empirical evidence for the extended theory, we urge others to replicate our study with larger samples before any firm conclusions are warranted. Future studies with larger samples might benefit from using a similar design to map offenders' time-specific activity spaces, especially if also more serious offenders with longer offense histories are included. We believe that the use of our online survey instrument has a great advantage over previous register based studies, as we were able to study a much wider range of activity nodes than those usually included and we were able to capture the time of day offenders usually visited their activity nodes. Another way forward might be to use smartphone applications to track the whereabouts of people (see e.g., Ruiter & Bernasco, 2018) or other type of GPS-tracking data (e.g., Rossmo et al., 2012). These methodologies can be used to even more comprehensively measure offenders' activity spaces, such as a wider range of routine activities as well as the routinely travelled paths between activity nodes.

When such new data get collected, it is worthwhile to assess whether the distinction between planned and opportunistic crimes can more explicitly be taken into account. For example, an opportunistic offender might seize some crime opportunity on the way to work and the timing of crime will then be around the start of the working day. For crimes that require more planning, we expect that the mechanism as proposed in our extended theory is at play: offenders acquire knowledge of their environment during ordinary daily routine activities that only at certain times is applicable for the commission of crime in other situations. However, this might also depend on the specific type of offense involved. We can imagine, for example, that bank robbers would go to some lengths to familiarize themselves with the area around the target bank before committing the offense, which may well be some way from their activity spaces. Although we did not measure the exact degree of planned and opportunistic behavior for our offender group, our online questionnaire included a question about whether the offender was at the specific place and time of the crime in order to commit the crime or for some other reason. We observe that the percentage of planned offenses that were committed inside and outside of the offenders' activity space were quite comparable (25.6% and 32.1%, respectively). In this regard, it would also be interesting to further distinguish between different types of crime. Unfortunately, our small sample size prohibits any further disaggregation.

To conclude, we introduced an extended crime pattern theory to understand both the spatial and temporal patterns in crime and we put it to a first empirical test. Although we found tentative support for our extended theory, it is for future studies with larger samples to replicate our research and shed more light on the specific mechanisms behind the theory.



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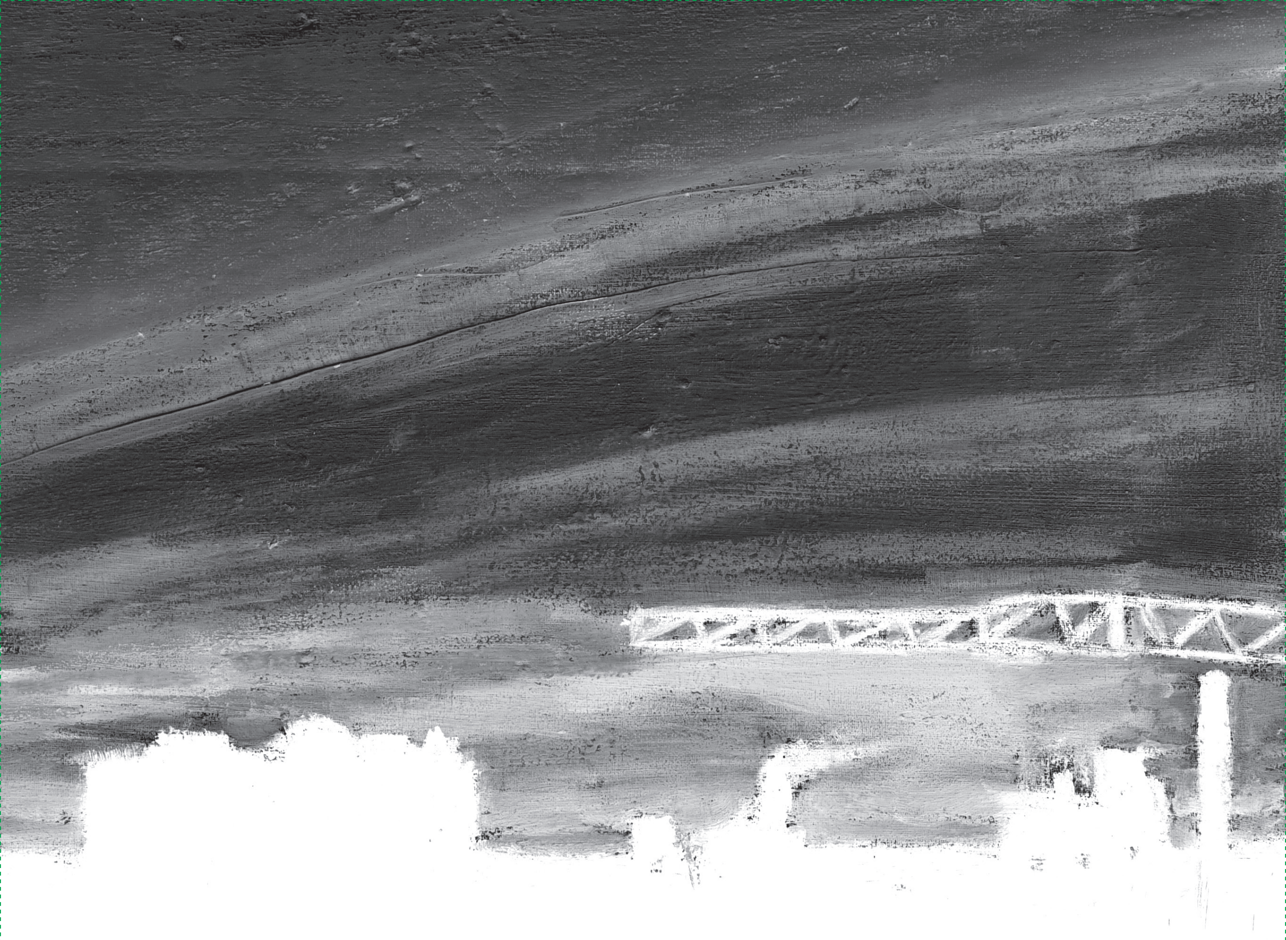
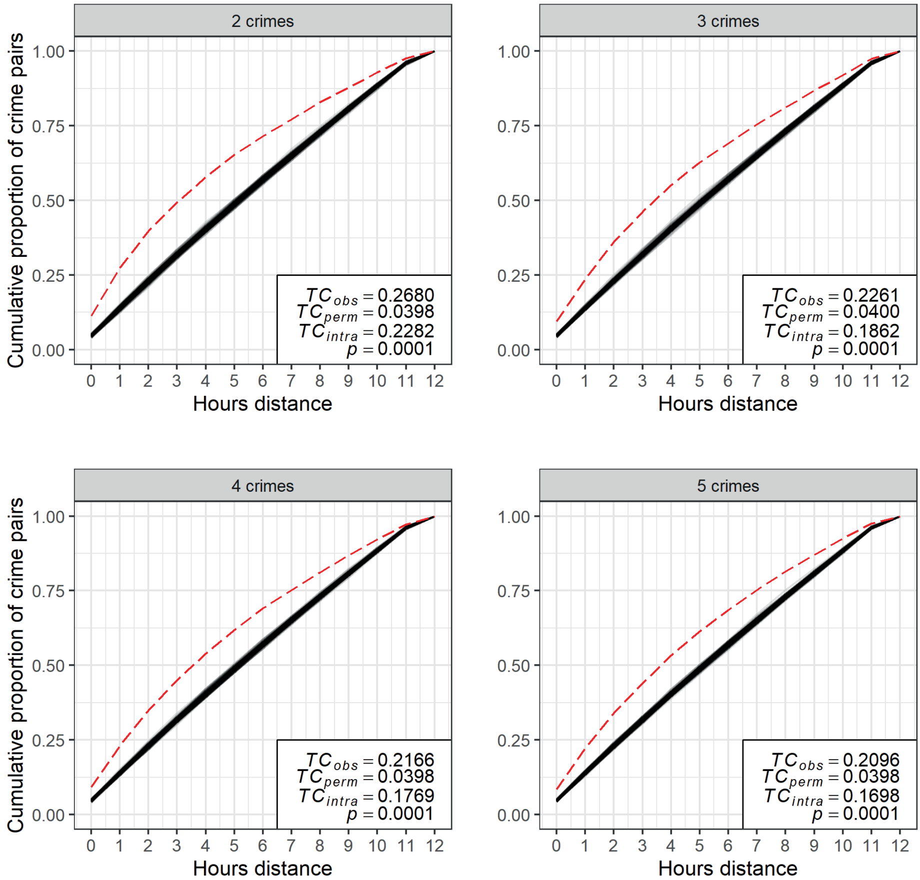
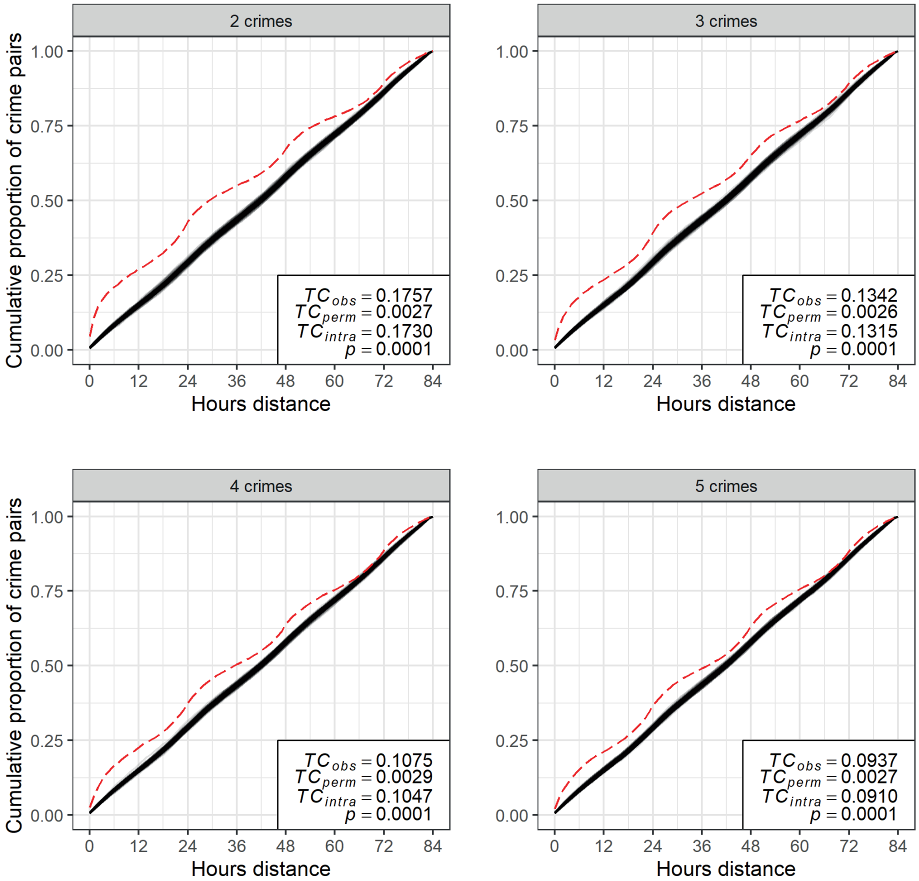


Appendices

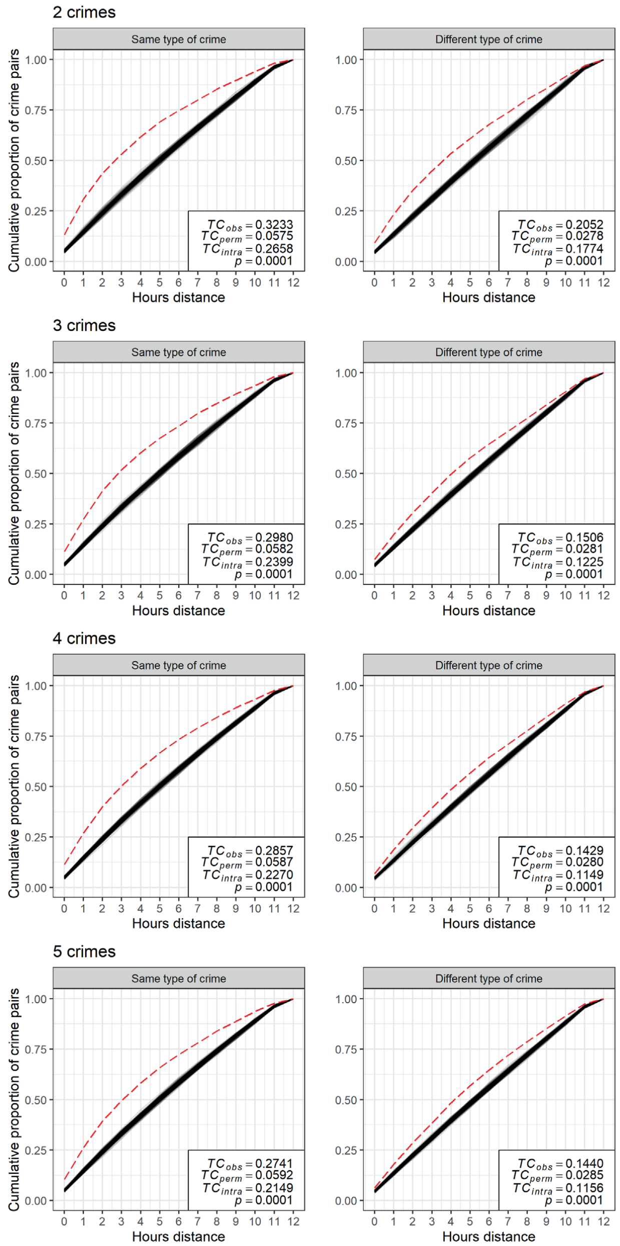
Appendices for Chapter 2



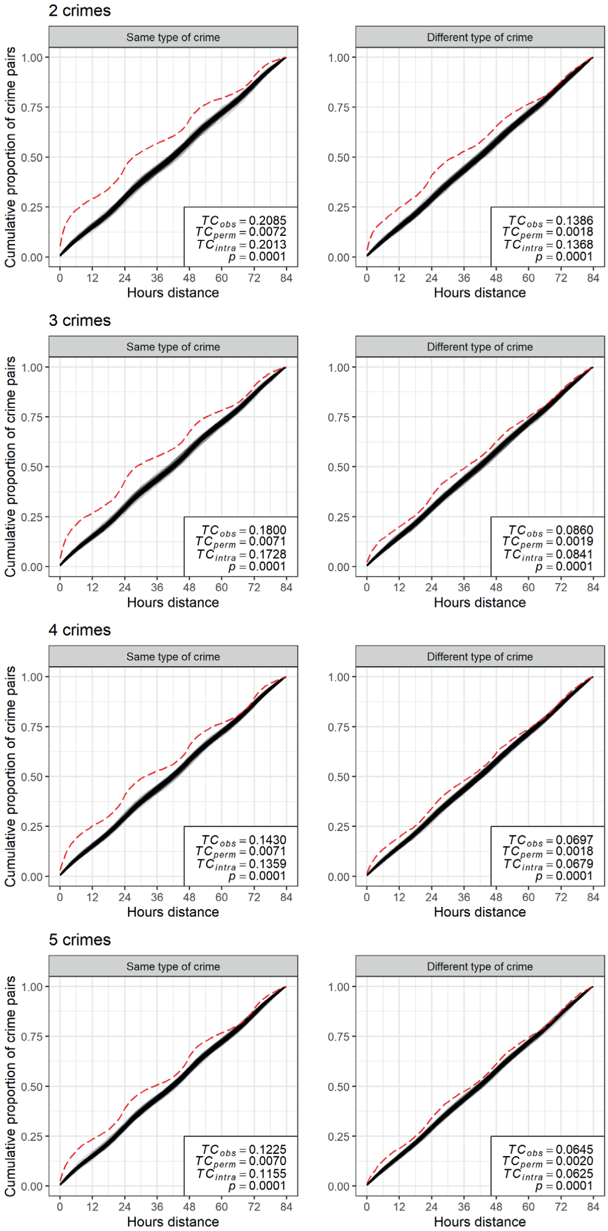
Appendix A1. Hour of day consistency for offenders with 2-5 crimes.



Appendix A2. Hour of week consistency for offenders with 2-5 crimes.



Appendix B1. Hour of day consistency by crime type similarity for offenders with 2-5 crimes.



Appendix B2. Hour of week consistency by crime type similarity for offenders with 2-5 crimes.

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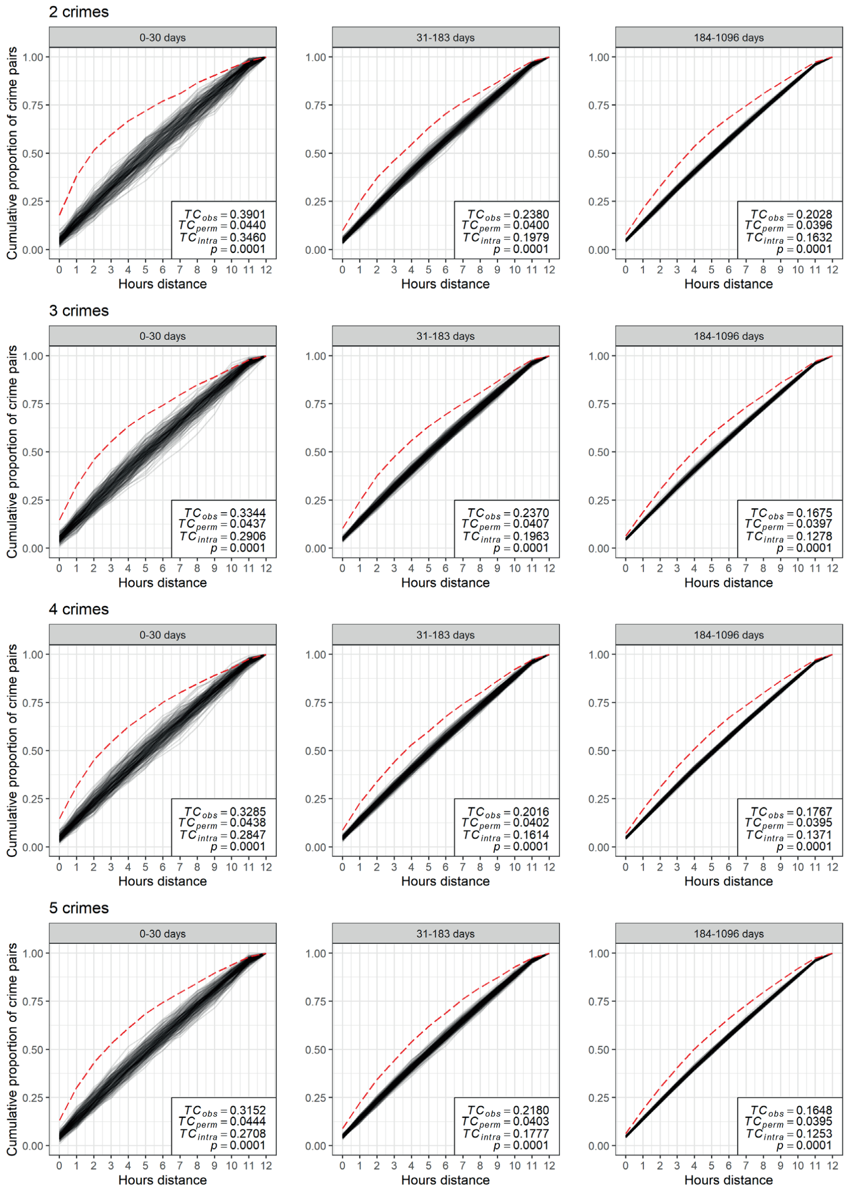
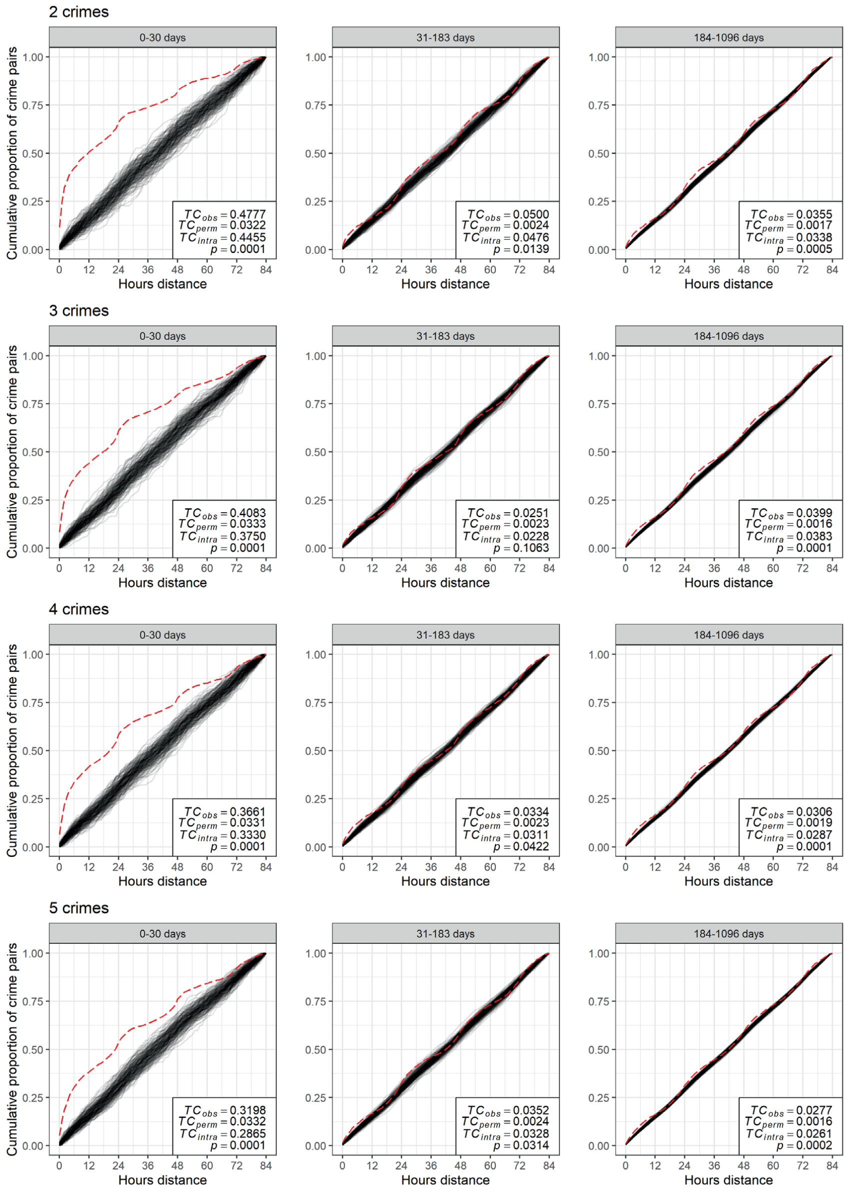


Appendix C1. Hour of day consistency by recency for offenders with 2-5 crimes.



Appendix C2. Hour of week consistency by recency for offenders with 2-5 crimes.

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Appendices for Chapter 3

Table 3.3 Conditional logit model testing the association of different routine activity domains and offenders' crime time choices (*N* = 31 crimes without theft from shop/shoplifting * 56 possible 3-hour time slots of the week = 1,736).

Variable	**OR**	**SE**	**Z**	**P**
Routinely spent time at/on ...				
... Home	1.610	1.109	0.69	0.489
... Work	2.281	1.663	1.13	0.258
... Education	0.977	7.620	-0.00	0.998
... Sports	0.408	2.471	-0.15	0.882
... Shopping	2.748	4.691	0.59	0.554
... Going out	3.168	23.560	0.16	0.877
... Other activity	0.837	3.975	-0.04	0.970
Pseudo-R^2	0.03			

Note: OR = odds ratio coefficient; SE = bootstrapped cluster-corrected standard error; Reference category (if all study variables score 0) = offender is not usually engaged in any routine activity during specific time slot.

Table 3.4 Conditional logit model testing the association of different routine activity domains and offenders' crime time choices (*N* = 60 crimes * +/- 42 possible 3-hour 'no sleeping' time slots of the week = 2,591).

Variable	**OR**	**SE**	**Z**	**P**
Routinely spent time at/on ...				
... Home	0.412	0.200	-1.83	0.068
... Work	0.966	1.603	-0.02	0.983
... Education	2.479	7.234	0.31	0.756
... Sports	1.850	4.082	0.28	0.780
... Shopping	5.830	2.176	4.72	0.001
... Going out	0.465	1.854	-0.19	0.848
... Other activity	1.255	5.329	0.05	0.957
Pseudo-R^2	0.09			

Note: OR = odds ratio coefficient; SE = bootstrapped cluster-corrected standard error; Reference category (if all study variables score 0) = offender is not usually engaged in any routine activity during specific time slot.

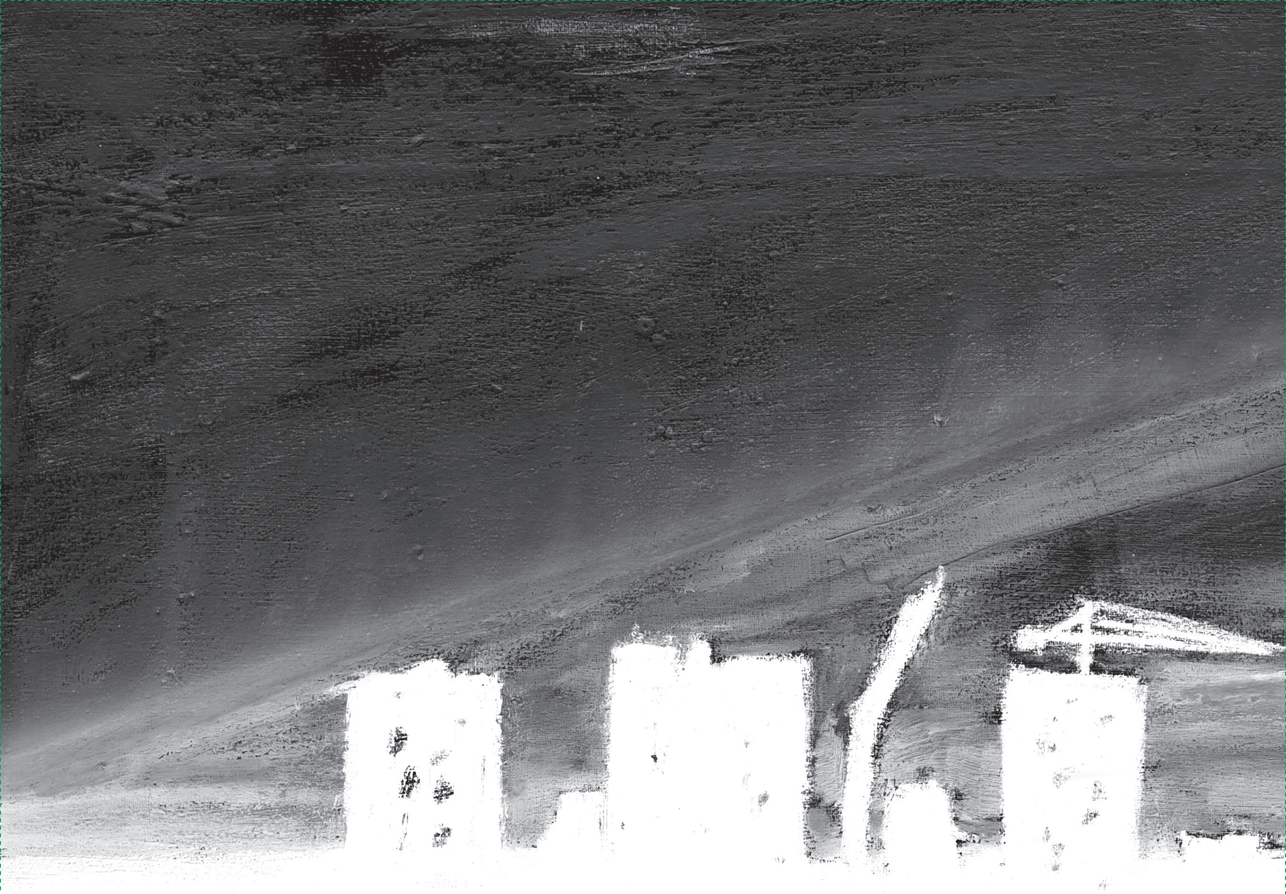
Appendix for Chapter 5

Table 5.3 Conditional logit model testing the effects of time-varying activity spaces on crime location choice (N = 71 crimes * 13,305 possible neighborhoods = 944,655).

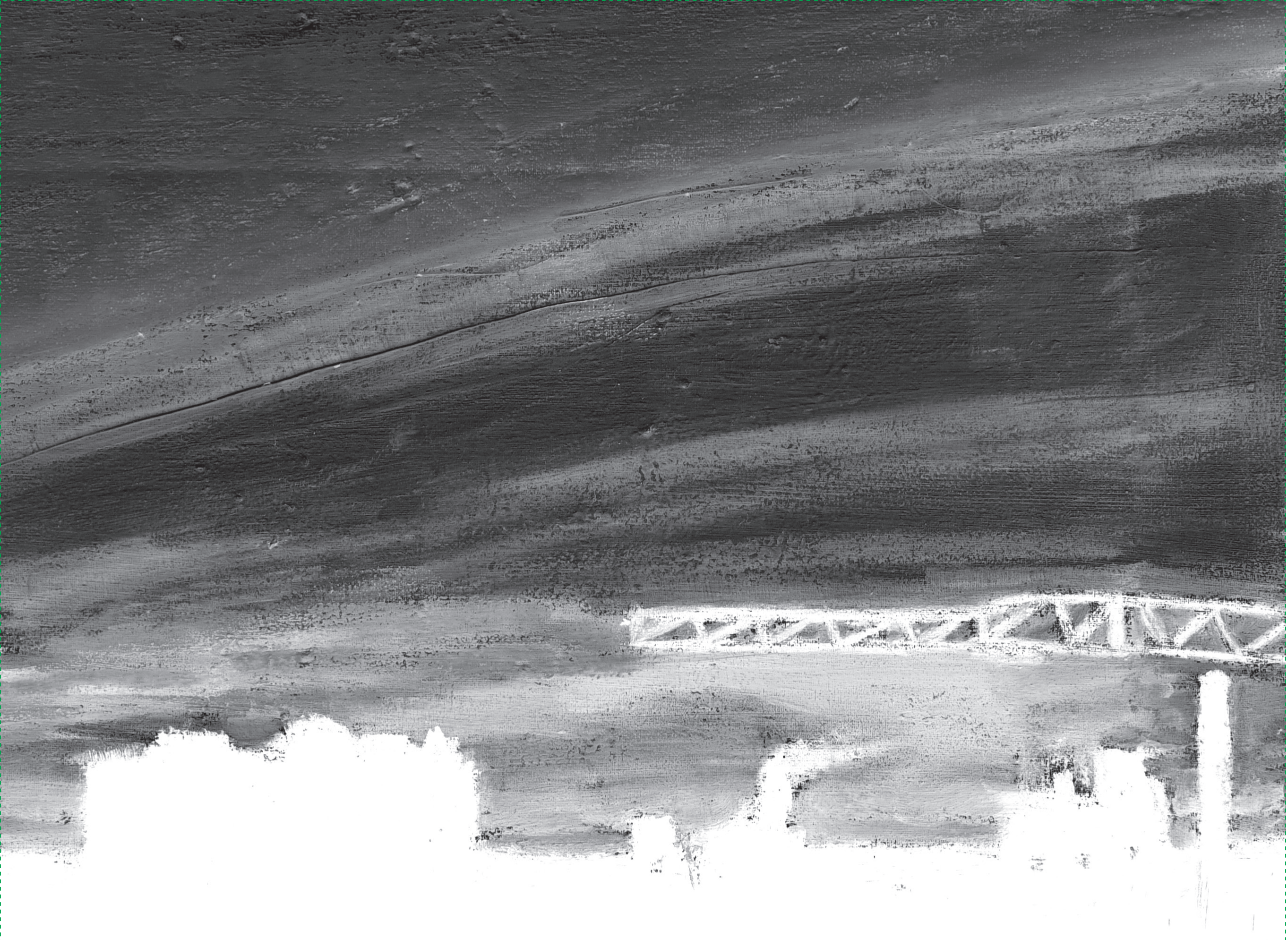
Variable	OR	SE	Z	P
Neighborhood routinely visited at ...				
... Both same and different time of day as crime event	3145.23	2340.03	10.82	0.001
... Only same time of day as crime event	1966.20	942.02	15.83	0.001
... Only different time of day as crime event	1204.35	8108.26	1.05	0.292
Pseudo-R^2	0.27			

Note: OR = odds ratio coefficient; SE = bootstrapped cluster-corrected standard error.

A



S



Nederlandse samenvatting

(Dutch summary)

Introductie

Criminologen bestuderen al bijna twee eeuwen de vraag waar en wanneer delicten worden gepleegd. Volgens een van de centrale theorieën in de omgevingscriminologie, *crime pattern theory* (Brantingham & Brantingham, 1981; 2008; Brantingham et al., 2017), plegen daders delicten op plekken waar aantrekkelijke doelwitten samenvallen met hun individuele *awareness space*. Deze awareness space bestaat uit de belangrijkste plekken waar mensen tijdens hun dagelijkse bezigheden komen, zoals woning, werk, school en recreatie, en de routes tussen deze plekken. Eerder onderzoek laat zien dat daders hun delicten vaak plegen dicht bij hun huidige of eerdere woning, of in de buurt van woningen van naaste familieleden. Ook blijkt dat recidivisten geneigd zijn om terug te keren naar locaties waar ze in het verleden al hebben toegeslagen. Tot op heden heeft crime pattern theory en het gerelateerde empirische onderzoek in de omgevingscriminologie zich voornamelijk bezig gehouden met de keuzes van daders over *waar* zij hun delicten plegen. Zij hebben echter nauwelijks aandacht besteed aan de *timing* van die ruimtelijke doelwitkeuzes of de vraag waarom daders ervoor kiezen om op bepaalde tijdstippen juist wel of niet toe te slaan. Eerder onderzoek ging er impliciet vanuit dat daders zich op verschillende momenten van de dag en verschillende dagen van de week in gelijke mate bewust zijn van criminele mogelijkheden en dus op elk moment van de dag of week evenveel kans hebben om delicten te plegen op alle mogelijke plaatsen binnen hun awareness space.

In dit proefschrift trekken we deze onrealistische veronderstelling in twijfel door de bestaande theorie te verbeteren en verschillende hypothesen afgeleid uit de verbeterde theorie te testen aan de hand van een combinatie van reeds bestaande en nieuw verzamelde gegevens. We beargumenteren dat de ruimtelijke kennis die een dader opdoet tijdens zijn dagelijkse routines of tijdens het plegen van eerdere delicten niet in gelijke mate geldt voor alle tijdstippen van de dag, maar vooral voor de tijdstippen dat deze plekken gewoonlijk door de dader worden bezocht. Want waarom zou een dader weten of een bepaalde plek aantrekkelijk is om overdag een inbraak te plegen, wanneer hij die plek alleen ‘s avonds bezoekt? Of wat kan een dader zeggen over de aantrekkelijkheid van een locatie voor een overval op een doordeweekse dag, terwijl hij daar zelf alleen in het weekend komt? Om de algemene ruimtelijk-temporele patronen van criminaliteit te kunnen verklaren, moeten we een verschuiving maken van waarnemingen op het niveau van de samenleving als geheel naar een daderperspectief op individueel niveau. Het doel van dit proefschrift is niet om te beschrijven waar en wanneer delicten plaatsvinden, maar om verklaringen te ontwikkelen en te testen voor de vraag waarom daders op die specifieke plaatsen en tijdstippen delicten plegen (en niet op andere plaatsen en tijdstippen). De overkoepelende onderzoeksvraag luidt daarom als volgt: *Hoe kunnen we het ruimtelijk-temporele criminele keuzegedrag van daders verklaren*?

Met de bestaande data zoals gebruikt in de omgevingscriminologie kan deze vraag niet worden beantwoord. Hiervoor zijn nieuwe data nodig die meer inzicht geven in de tijdspecifieke routine activiteitenpatronen en het ruimtelijk-temporele keuzeproces van daders. Het is dus noodzakelijk om daders over deze patronen en hun gemaakte en potentiële keuzes te bevragen. In dit proefschrift maken we daarom gebruik van twee soorten databronnen. Ten eerste analyseren we grootschalige politiegegevens over een groot aantal daders van verschillende soorten type delicten en de specifieke dagen en tijdstippen waarop zij deze verschillende delicten hebben gepleegd. Daarnaast hebben we de individuele routine activiteitenpatronen van een groep daders in Nederland in kaart gebracht met behulp van een uniek online instrument: de Tijdspecifieke Activiteiten Survey (TAS) die we speciaal voor deze studie hebben ontworpen. Hierin rapporteerden 30 daders over de specifieke tijdstippen waarop zij in het afgelopen jaar hun belangrijkste routine activiteiten bezochten, zoals school, werk en verschillende recreatieve activiteiten. Daarnaast beschreven zij de locaties en tijdstippen waarop zij hun 71 gerapporteerde delicten hebben gepleegd, waaronder voertuigdiefstal, winkeldiefstal, mishandeling en vandalisme.

Bevindingen

Als eerste stap in het beantwoorden van de overkoepelende onderzoeksvraag beginnen we in hoofdstuk 2 met het in kaart brengen van de mate van temporele consistentie in de delictpatronen van individuele daders. Om te onderzoeken of daders hun delicten op vergelijkbare tijdstippen van de dag en week plegen hebben we voor dit hoofdstuk zelf een nieuwe test ontwikkeld. In hoofdstuk 3 gebruiken we een keuzemodel uit de economie om de temporele beslissingen van daders te verklaren en bestuderen we de rol van verschillende soorten routine activiteiten in het criminele besluitvormingsproces. In de laatste twee hoofdstukken van dit proefschrift stellen we onze uitgebreide crime pattern theory op de proef en onderzoeken we in hoeverre daders terugkeren naar eerdere delictlocaties op vergelijkbare tijdstippen van de dag of vergelijkbare dagen van de week (zie hoofdstuk 4) en in hoeverre daders hun delicten plegen in routinematig bezochte gebieden op specifieke tijdstippen van de dag (zie hoofdstuk 5). Hieronder volgen de belangrijkste bevindingen in een korte samenvatting per hoofdstuk.

Hoofdstuk 2: Wanneer plegen daders hun delicten? Een analyse van de temporele consistentie in individuele delictpatronen

Hoewel veel daders slechts één delict plegen (waarvan de politie op de hoogte is), plegen sommige daders in de loop van hun criminele carrière meerdere delicten. Eerder onderzoek heeft al aangetoond dat dergelijke recidivisten zeer consistent zijn in *waar* zij delicten plegen, maar het is nog onbekend of daders ook herhaaldelijk delicten plegen op een vergelijkbaar tijdstip of dag van de week. Onderzoek naar menselijke mobiliteit laat zien dat routine activiteiten duidelijk verschillen van persoon tot persoon, maar dat individuele patronen sterk terugkerende dagelijkse en wekelijkse ritmes laten zien. Omdat daders, slachtoffers en zogenaamde *guardians* (personen die criminaliteit kunnen helpen voorkomen door hun aanwezigheid) allemaal onderhevig zijn aan temporele beperkingen in hun dagelijkse tijdsbesteding als gevolg van belangrijke routine activiteiten, stellen we in hoofdstuk 2 dat daders mogelijk ook consistentie vertonen in de timing van hun delicten en deze dus op ongeveer dezelfde momenten van de dag en van de week plegen. We verwachten dat voor een dader die bijvoorbeeld op woensdagmiddag zijn eerste delict heeft gepleegd de kans groter is dat hij zijn tweede delict opnieuw op een woensdagmiddag pleegt dan op een vrijdag- of zaterdagavond. De onderzoeksvraag van dit hoofdstuk luidt: *In hoeverre plegen recidivisten hun delicten op vergelijkbare uren van de dag en vergelijkbare uren van de week?*

Met behulp van grootschalige politiegegevens analyseren we de delictgeschiedenis van recidivisten uit de regio Den Haag. Aangezien wij willen kwantificeren in welke mate dezelfde daders op dezelfde dagen en tijdstippen delicten plegen, moeten wij het effect van de tijdsvariërende aantrekkelijkheid van geschikte doelwitten voor criminaliteit eruit filteren. Met een Monte Carlo permutatietest hebben we getoetst in hoeverre recidivisten hun delicten op vergelijkbare uren van de dag en vergelijkbare uren van de week plegen, bovenop wat kan worden verwacht op basis van de algemene temporele spreiding van de delicten in de politiegegevens. De resultaten laten zien dat recidivisten een sterke temporele consistentie vertonen: zij plegen hun delicten op meer vergelijkbare uren van de dag en week dan verwacht. Bovendien zijn de waargenomen patronen van temporele consistentie sterker voor delicten van hetzelfde type criminaliteit dan voor delicten van verschillende typen criminaliteit. De temporele consistentiepatronen blijken ook sterker te zijn naarmate de tijdspanne tussen de delicten korter is. Op basis van de uitkomsten kunnen we concluderen dat eerdere studies al aantoonden dat daders consistent zijn in hun ruimtelijke criminele keuzegedrag, maar dat de huidige studie laat zien dat ze daarnaast ook zeer consistente temporele keuzes maken met betrekking tot hun delictgedrag.

Hoofdstuk 3: Criminele tijdstipkeuze: de rol van discretionaire en non-discretionaire routine activiteiten in het temporele keuzegedrag van daders

De vraag waarom daders hun delicten op bepaalde tijdstippen plegen is tot op heden nogal onderbelicht gebleven in de omgevingscriminologie. Aangezien routine activiteiten sterke temporele beperkingen opleggen aan daders, stellen ze ook grenzen aan hun deelname aan andere activiteiten, zoals het plegen van delicten, gedurende bepaalde tijdsperioden. Hoewel verschillende etnografische studies de routine activiteitenpatronen van daders in relatie tot hun criminele gedrag hebben onderzocht, beperkten deze studies zich tot kleinschalige interviews met enkel professionele inbrekers. In hoofdstuk 3 combineren we daarom de tijdskeuzes van een groep daders van verschillende type delicten met een gedetailleerde beschrijving van hun temporele routine activiteitenpatronen. We maken hierbij onderscheid tussen discretionaire routine activiteiten die vrijwillig of minder tijdsgebonden zijn (zoals winkelen of uitgaan) en non-discretionaire routine activiteiten die over het algemeen meer rigide tijdsvensters hebben waarin ze moeten worden uitgevoerd (zoals naar werk of school gaan). We verwachten dat de discretionaire aard van eerstgenoemde activiteiten meer flexibiliteit biedt om plannen te wijzigen en in plaats daarvan een delict te plegen. De onderzoeksvraag van dit hoofdstuk luidt: *In hoeverre is de kans dat daders delicten plegen kleiner op momenten dat ze routinematig bezig zijn met een non-discretionaire activiteit dan op momenten dat ze routinematig bezig zijn met een discretionaire activiteit?*

Om onze hypothesen te testen maken we gebruik van de door ons ontwikkelde Tijdspecifieke Activiteiten Survey (TAS). In deze online vragenlijst hebben we informatie verzameld over de specifieke tijdstippen van de dag waarop daders routinematig een breed scala aan zowel non-discretionaire activiteiten (d.w.z. de domeinen werk en school) als discretionaire activiteiten (d.w.z. de domeinen thuis, sport, winkelen, uitgaan en andere activiteiten) bezochten. In tegenstelling tot onze verwachtingen konden wij niet aantonen dat daders minder vaak delicten plegen op tijdstippen waarop zij gewoonlijk bezig waren met routine activiteiten dan op tijdstippen waarop zij dat niet waren. Ook konden wij niet aantonen dat daders minder vaak delicten plegen op tijdstippen waarop zij routinematig bezig waren met non-discretionaire activiteiten dan op tijdstippen waarop zij routinematig bezig waren met discretionaire activiteiten. Terwijl studies naar ruimtelijke locatiekeuzes consequent hebben aangetoond dat de locaties die daders regelmatig bezoeken voorspellend zijn voor waar ze delicten plegen, vinden wij in deze studie geen bewijs voor de verwachting dat de tijdstippen waarop ze gewoonlijk bezig zijn met (non-)discretionaire routine activiteiten voorspellend zijn voor de specifieke tijdstippen van de dag waarop ze hun delicten plegen.

Hoofdstuk 4: De juiste tijd voor een delict? Temporele aspecten in de locatiekeuze van recidivisten

Eerder onderzoek heeft aangetoond dat daders een grotere kans hebben om delicten te plegen in gebieden waar ze in het verleden al hebben toegeslagen dan in gebieden die nooit eerder het doelwit waren. Voortbouwend op deze literatuur onderwerpen we in hoofdstuk 4 onze uitgebreide crime pattern theory aan een eerste empirische test, maar alleen met betrekking tot het idee dat de vorige delictlocatie op een bepaald tijdstip van de dag of week informatief is voor het volgende delict. We onderzoeken de relatie tussen het terugkeren naar gebieden die eerder doelwit waren en het tijdstip waarop daders hun delicten plegen. We verwachten dat wanneer daders door eerdere delicten op de hoogte raken van criminele kansen en mogelijkheden, hun kennis over de aantrekkelijkheid van deze eerder bezochte gebieden niet in alle situaties in dezelfde mate van toepassing is, omdat de potentiële risico's en beloningen verschillen tussen overdag en 's nachts. Dit kan weer van invloed zijn op de locaties die de daders vervolgens kiezen voor het plegen van een delict. De onderzoeksvraag van dit hoofdstuk luidt: *In hoeverre zijn de locatiekeuzes van recidivisten afhankelijk van het tijdstip van de delicten binnen de week en binnen de dag?*

Politiegegevens over een grote groep recidivisten in Nederland zijn geanalyseerd met behulp van ruimtelijke discrete keuzemodellen, die ons in staat stellen om tegelijkertijd de invloed van zowel doel- als daderkenmerken op de criminele doelwitselectie te bestuderen. De individuele beslisser is de dader en de afhankelijke variabele is de ruimtelijke keuze-uitkomst: het zogenaamde 'keuzealternatief' (d.w.z. de buurt waar het delict wordt gepleegd) dat de dader heeft gekozen uit een telbare set van alternatieve locaties (d.w.z. alle buurten waar het delict had kunnen worden gepleegd). De resultaten laten zien dat daders een veel grotere kans hebben om terug te keren naar buurten waar ze in het verleden al hebben toegeslagen wanneer ze het delict plegen op een vergelijkbare dag van de week of een vergelijkbaar tijdstip van de dag in vergelijking met een andere dag of een ander tijdstip. Bovendien zijn de effecten sterker voor delicten van hetzelfde type criminaliteit dan voor verschillende types. Deze bevindingen bieden ondersteuning voor onze uitgebreide crime pattern theory, waarin we veronderstelden dat de toepasbaarheid van ruimtelijke kennis in de awareness space van daders (gemeten als eerdere delictlocaties) verschilt over de dag en de week. Op basis van deze studie kunnen we concluderen dat voor een beter begrip van het ruimtelijke keuzegedrag van daders in toekomstig onderzoek rekening gehouden moet worden met zowel de eerdere delictlocaties van daders als de tijdstippen binnen de dag en binnen de week waarop de delict werden gepleegd.

Hoofdstuk 5: Juiste plaats, juiste tijd? Criminaliteitspatronen theorie tijdspecifiek maken

In hoofdstuk 4 hebben we betoogd dat recidivisten tijdspecifieke kennis opdoen over hun delictlocaties en daardoor meer geneigd zijn om op hetzelfde tijdstip van de dag of op dezelfde dag van de week terug te keren naar gebieden waar ze in het verleden al hebben toegeslagen. In hoofdstuk 5 veralgemenen we dit idee tot alle daders en andere belangrijke locaties voor routine activiteiten, door het concept van de awareness space opnieuw te definiëren: voortbouwend op onze uitgebreide crime pattern theory stellen wij dat de toepasbaarheid van ruimtelijke kennis in de gehele awareness space tijdspecifiek is, niet alleen voor eerdere delictlocaties. Dit impliceert dat de verworven kennis van geschikte doelwitten in bepaalde gebieden het meest van toepassing is op de tijdstippen waarop deze gebieden door de daders tijdens hun dagelijkse routine activiteiten werden bezocht (ongeacht of zij in deze gebieden criminaliteit hebben gepleegd). De onderzoeksvraag in het slothoofdstuk van dit proefschrift luidt: *In hoeverre plegen daders delicten in gebieden die zij routinematig op hetzelfde tijdstip van de dag hebben bezocht in vergelijking met gebieden die zij routinematig op verschillende tijdstippen van de dag hebben bezocht?*

In dit laatste hoofdstuk maken we gebruik van het Tijdspecifieke Activiteiten Survey (TAS). Dit stelt ons in staat om een breder scala van routine activiteiten te bestuderen die beter aansluiten bij het concept van awareness space, zoals school, werk en een verscheidenheid aan verschillende vrijetijdsactiviteiten. We onderzoeken de specifieke tijdstippen van de dag waarop een groep daders in het afgelopen jaar hun belangrijkste routine activiteiten bezochten, evenals het tijdstip en de locatie van hun zelf-gerapporteerde overtredingen in het afgelopen jaar. De resultaten van het discrete keuzemodel suggereren dat daders een grotere kans lijken te hebben om delicten te plegen in buurten die zij routinematig op hetzelfde tijdstip van de dag bezochten dan in buurten die zij routinematig op verschillende tijdstippen bezochten – hoewel het verschil in onze kleine steekproef niet statistisch significant was. Op basis van de bevindingen van deze studie kunnen we concluderen dat onze uitbreiding van crime pattern theory slechts voorzichtig wordt ondersteund. We stelden dat de awareness spaces van daders niet alleen ruimtelijk variëren zoals de oorspronkelijke theorie suggereert, maar dat de toepasbaarheid ook temporeel varieert. Dit als gevolg van het feit dat daders op bepaalde tijdstippen van de dag routine activiteiten bezoeken en daarmee tijdspecifieke kennis opdoen (die het beste aansluit bij die tijdstippen) over de locaties van aantrekkelijke doelwitten. De resultaten van dit slothoofdstuk suggereren inderdaad voorzichtig dat het tijdstip van regulier bezoek en tijdstip van delict vaak samenvallen, maar ook dat replicatieonderzoek met grotere steekproeven nodig is voordat er definitieve conclusies kunnen worden getrokken.

Conclusie

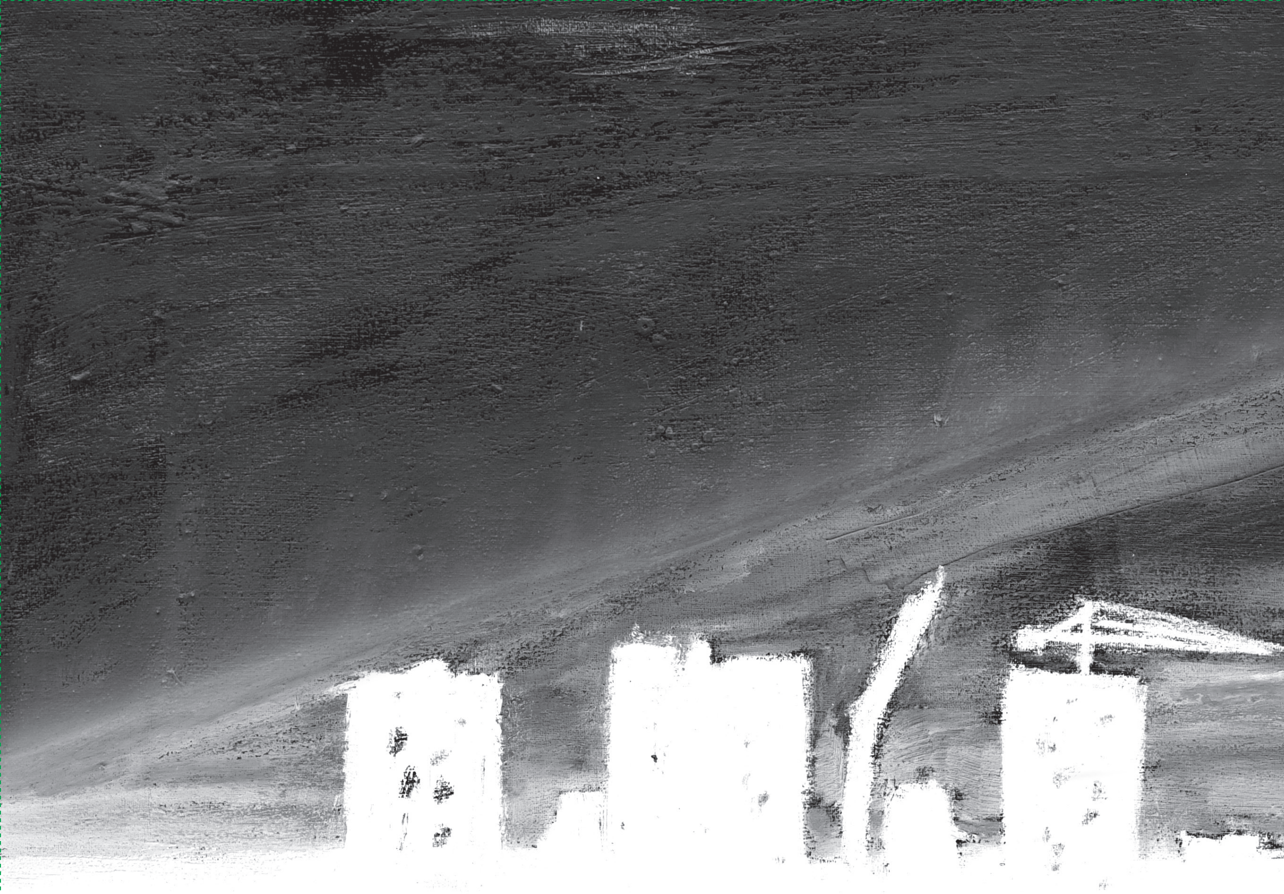
Een eerste algemene conclusie is dat de tijdsvariërende awareness space van daders moet worden opgenomen in crime pattern theory. Volgens deze theorie plegen daders delicten op die plaatsen waar hun individuele awareness spaces overlappen met aantrekkelijke doelwitten. Zowel de theorie als gerelateerd empirisch onderzoek in de omgevingscriminologie zijn tot op heden nogal atemporeel gebleven, alsof de timing van de routine activiteiten van daders en hun delicten geen rol speelt. Dit proefschrift verbetert de oorspronkelijke theorie en stelt een tijdspecifieke uitbreiding voor: de ruimtelijke kennis die daders opdoen tijdens dagelijkse routine activiteiten is niet op alle tijdstippen van de dag of dagen van de week in gelijke mate toepasbaar. Dit is van invloed op de locaties die zij vervolgens kiezen om hun delict te plegen. Op basis van de resultaten uit hoofdstuk 4 en 5 kunnen we concluderen dat de kennis die daders hebben opgedaan van een buurt op een bepaald tijdstip door het plegen van eerdere delicten in die buurt (zoals aangetoond in hoofdstuk 4) of door het bezoeken van routine activiteitenlocaties in die buurt (zoals aangetoond in hoofdstuk 5), samenhangt met het plegen van delicten rond datzelfde tijdstip. De opgedane kennis van tijdsconstante kenmerken is natuurlijk van toepassing ongeacht het specifieke tijdstip, en een deel van de kennis die betrekking heeft op tijdsvariërende kenmerken kan ook worden gegeneraliseerd naar andere tijdstippen met behulp van eenvoudige heuristieken of mentale ‘shortcuts’. Hoewel een dader bijvoorbeeld bepaalde locaties voor routine activiteiten uitsluitend overdag bezoekt, kan hij misschien toch goede inschattingen maken over hoe de situatie ‘s nachts zou zijn (bijvoorbeeld op basis van aannames over regelmatige openings- en sluitingstijden). Hoofdstuk 5 laat inderdaad zien dat hoewel het routinematig bezoeken van buurten op bepaalde tijdstippen van de dag daders ruimtelijke kennis verschaft die het best van toepassing is op deze specifieke tijdstippen, deze kennis toch enigszins voorspellend is voor de locatiekeuzes van daders voor delicten op andere tijdstippen van de dag.

Een tweede conclusie van dit proefschrift is dat daders vrij consistent zijn in hun temporele keuzegedrag. Eerder onderzoek toonde al aan dat recidivisten zeer consistent zijn in waar zij delicten plegen, bijvoorbeeld wat betreft hun routinematig bezochte plaatsen, de afstand van hun woning tot de delictlocaties of de reisrichting vanuit huis. Uit hoofdstuk 2 blijkt bijvoorbeeld dat recidivisten ook een sterke temporele consistentie vertonen in hun individuele delictgedrag: zij plegen herhaaldelijk delicten op vergelijkbare uren van de dag en vergelijkbare uren van de week, meer dan op basis van de algemene temporele spreiding van de delicten in de politiegegevens mag worden verwacht. Een dader die bijvoorbeeld zijn eerste delict op maandagmiddag heeft gepleegd, heeft een grotere kans om zijn tweede delict opnieuw op maandagmiddag te plegen. Van een andere dader die zijn eerste delict op zaterdagavond heeft gepleegd is de kans groter dat hij zijn tweede delict opnieuw op zaterdagavond pleegt dan op een andere dag of een ander tijdstip. De resultaten van het discrete keuzemodel uit hoofdstuk 4 suggereren dat de kans om delicten te plegen in gebieden waar daders in het verleden al hebben toegeslagen veel groter is wanneer een recidivist het vorige delict in soortgelijke delen van de week of op soortgelijke tijdstippen van de dag heeft gepleegd dan wanneer het gebied eerder op andere tijdstippen van de week of de dag het doelwit was. Aan de hand van gedetailleerde informatie over de routine activiteiten en criminaliteitspatronen van daders uit de TAS-enquête blijkt uit de resultaten van hoofdstuk 5 dat niet alleen gebieden die eerder doelwit waren een groter risico lopen om op soortgelijke tijdstippen het doelwit te worden, maar ook gebieden die daders eerder op hetzelfde tijdstip van de dag routinematig hadden bezocht. Toekomstig onderzoek zou gebruik kunnen maken van de mechanismen op individueel daderniveau die in hoofdstuk 4 en hoofdstuk 5 van dit proefschrift zijn beschreven om voorspellingen te doen over de algemene ruimtelijke en temporele criminaliteitspatronen in de samenleving.

Een laatste algemene conclusie uit dit proefschrift is dat de ruimtelijk-temporele patronen in het keuzegedrag van daders verschillen afhankelijk van het type criminaliteit en de recentheid van de delicten. Aangezien zowel algemene routine activiteitenpatronen als gelegenheidsstructuren veranderen in de loop der tijd, verwachten we de sterkste temporele patronen binnen de dag en de week wanneer de delicten kort na elkaar worden gepleegd. De resultaten van hoofdstuk 2 laten zien dat dit inderdaad het geval is: de consistentiepatronen van de recidivisten in onze gegevens bleken sterker te zijn naarmate de tijdspanne tussen hun delicten korter was, vooral met betrekking tot delicten die binnen een maand werden gepleegd. Hoewel onze tijdspecifieke crime pattern theory een algemene verklaring biedt voor waar en wanneer daders hun delicten plegen, verschillen de gelegenheidsstructuren duidelijk voor verschillende soorten delicten. Dit betekent dat verschillende soorten delicten ook verschillende kennis vereisen over de tijdsafhankelijke aantrekkelijkheid van potentiële doelwitten. Hoewel bijvoorbeeld de aanwezigheid van bewoners of nabijgelegen buren een relevante factor is voor woninginbraak, is tijdspecifieke kennis hierover wellicht minder nuttig voor het plegen van een ander type delict met een heel andere gelegenheidsstructuur. In dit proefschrift laten we zien dat de temporele consistentiepatronen van daders (hoofdstuk 2) en de waarschijnlijkheid dat zij op vergelijkbare tijdstippen terugkeren naar gebieden waar zij eerder hebben toegeslagen (hoofdstuk 4) inderdaad sterker zijn voor delicten van hetzelfde type criminaliteit dan voor delicten van een ander type criminaliteit.

Door het uitbreiden en toetsen van een van belangrijkste theorieën in de omgevingscriminologie is de bijdrage van dit proefschrift voornamelijk wetenschappelijk. Maar een beter begrip van het ruimtelijk-temporele keuzegedrag van daders kan ook praktische waarde hebben: het biedt aanknopingspunten voor het oplossen en voorkomen van criminaliteit. Ten eerste zouden de uitkomsten van het onderzoek waardevol kunnen zijn voor het ontwerpen van interventies om recidive onder ex-gedetineerden te verminderen. De reclassering zou bijvoorbeeld re-integratieprogramma's kunnen uitvoeren die de eerdere ruimtelijk-temporele criminaliteitspatronen van daders verstoren door het actief reguleren van de tijdstippen en locaties van hun huidige dagelijkse routines. Daarnaast zou een beter begrip van het ruimtelijk-temporele beslisgedrag van daders ook kunnen helpen bij het verbeteren van voorspellende politiemodellen ("predictive policing") en analyses voor het koppelen van misdaadgegevens ("crime linkage analysis"). De bevindingen van dit proefschrift laten bijvoorbeeld zien dat recidivisten vrij consistent zijn in hun criminele keuzegedrag met betrekking tot dagelijkse en wekelijkse temporele cycli: ze plegen hun delicten op vergelijkbare tijdstippen van de dag en de week (hoofdstuk 2), ze hebben een grotere kans om terug te keren naar gebieden die eerder doelwit waren op vergelijkbare dagen van de week en tijdstippen van de dag (hoofdstuk 4), en ze hebben een grotere kans om delicten te plegen in buurten die ze eerder routinematig hebben bezocht op vergelijkbare tijdstippen van de dag in vergelijking met andere tijdstippen van de dag (hoofdstuk 5). Ondanks het feit dat meer dan een decennium geleden al een voorspellend politiemodel is ontwikkeld dat rekening houdt met patronen in de specifieke tijdstippen van de dag voor herhaald slachtofferschap, houden veel van deze modellen vandaag de dag nog steeds geen rekening met dergelijke cyclische tijdspatronen. Het is daarom van belang dat toekomstige analyses de reeds bestaande ruimtelijk-temporele modellen combineren met de cyclische tijdsmaten binnen de week en dag die in dit proefschrift centraal staan.

De resultaten van dit proefschrift laten zien dat naast het bestaande onderzoek naar het ruimtelijke keuzegedrag van daders ook het bestuderen van de temporele besluitvorming en de praktische implicaties daarvan belangrijk zijn. Toekomstig onderzoek kan de verschillende ruimtelijk-temporele aspecten in het keuzegedrag van daders die in de vier empirische hoofdstukken van dit proefschrift zijn besproken combineren, bijvoorbeeld door de keuzes van daders ten aanzien van de tijd en plaats van het delict gezamenlijk te onderzoeken. Op deze manier kunnen we de overkoepelende onderzoeksvragen binnen de omgevingscriminologie—waarom daders hun delicten juist op die locaties en tijdstippen plegen—beter beantwoorden. Uiteindelijk kan het begrijpen van de juiste plaats en het juiste tijdstip voor een delict bijdragen aan een veiligere toekomst.



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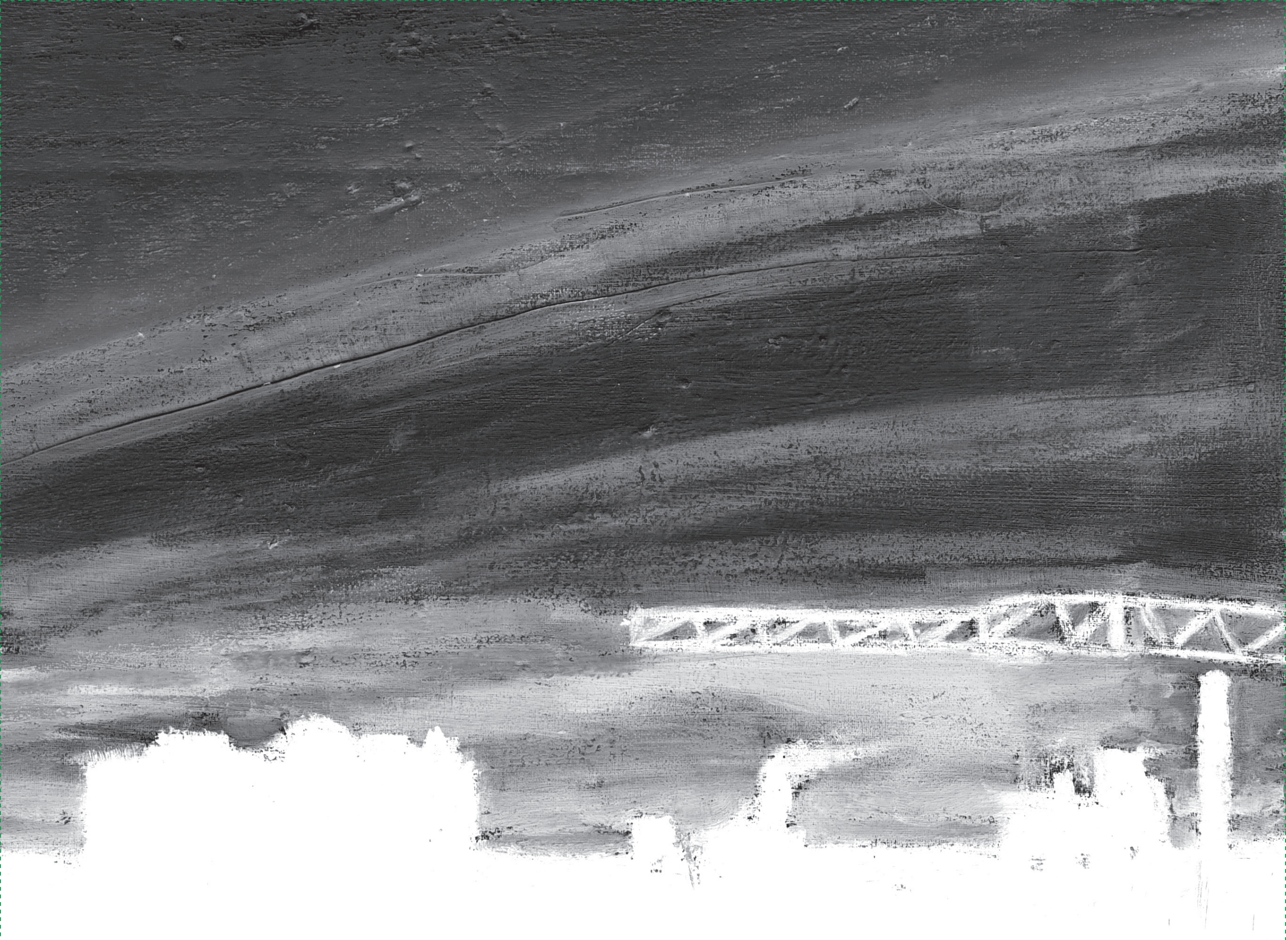

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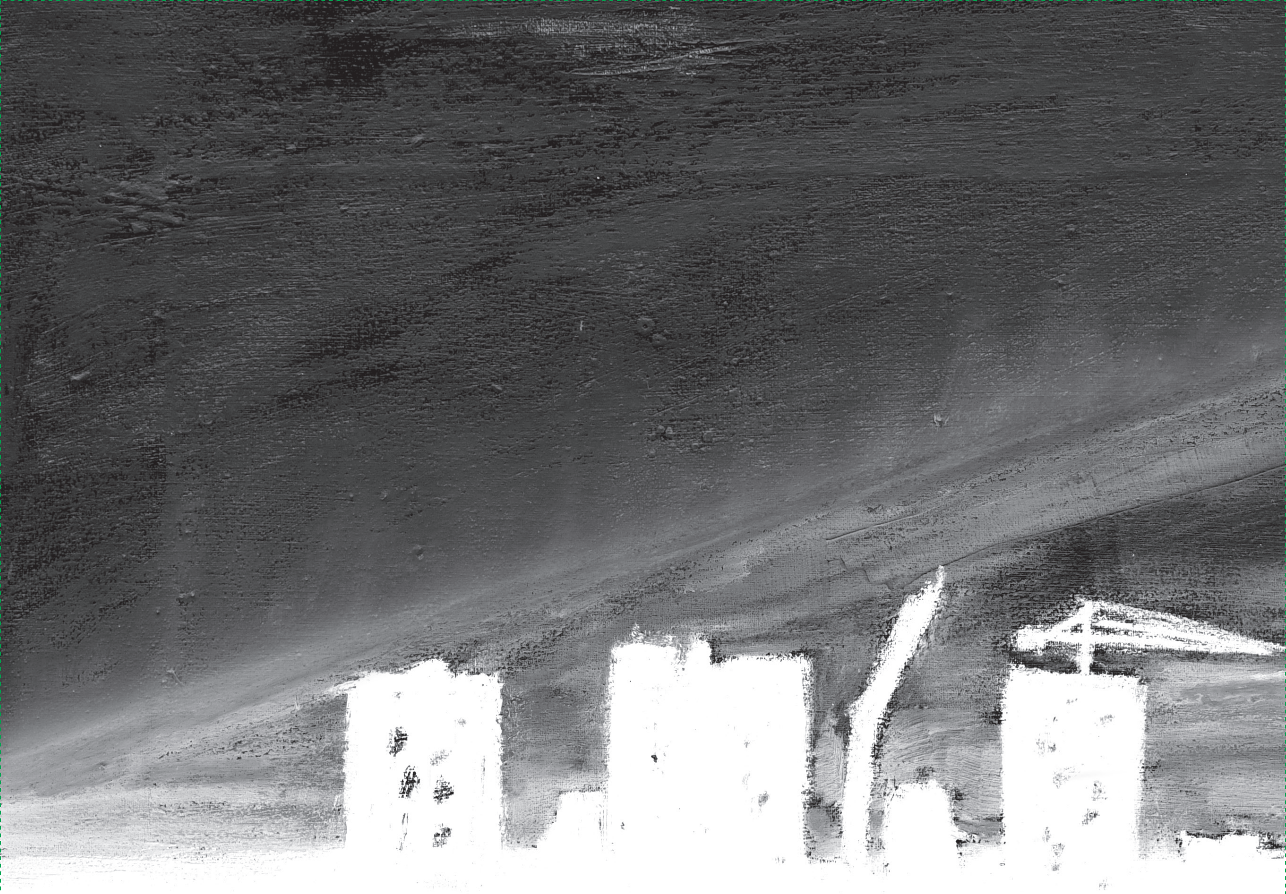

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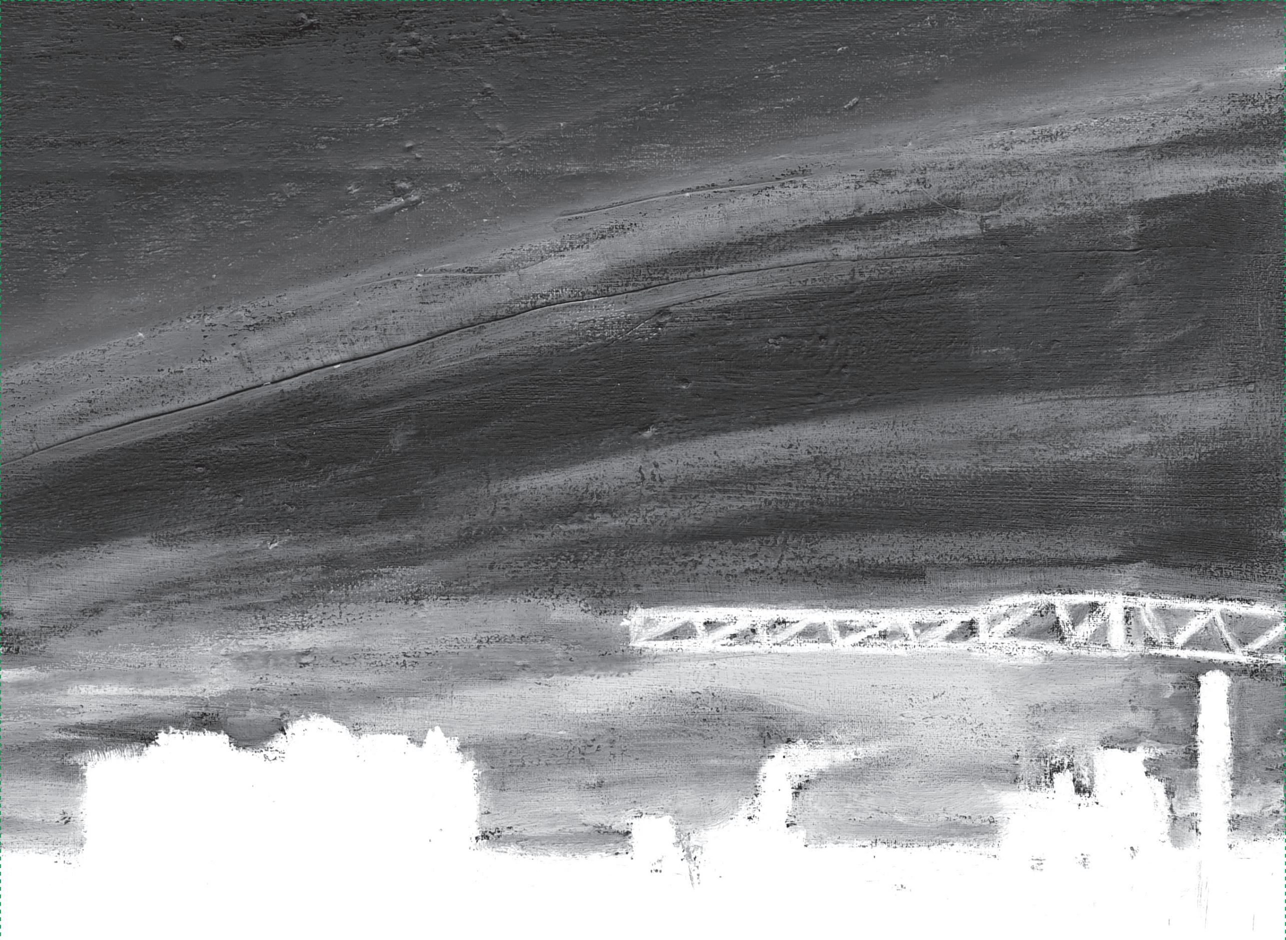

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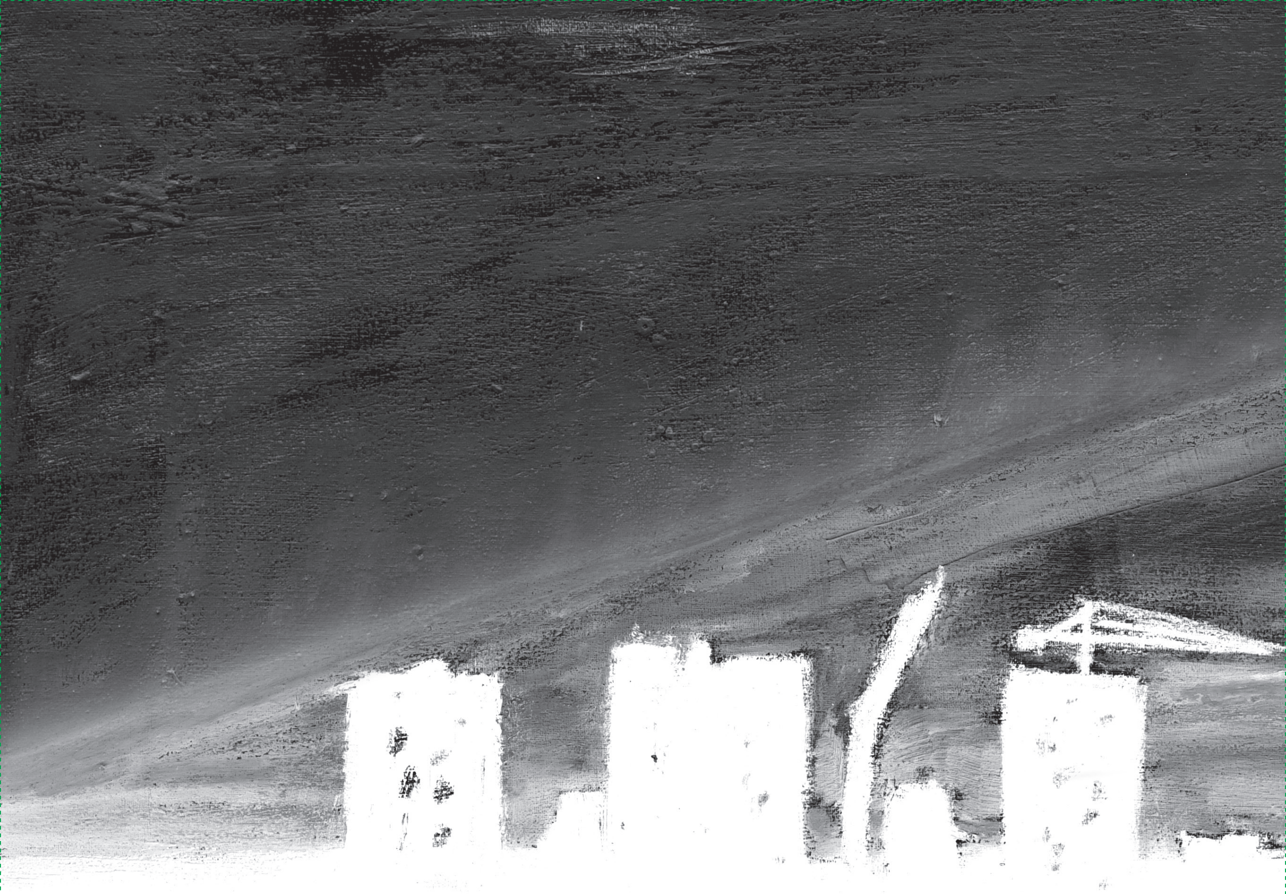

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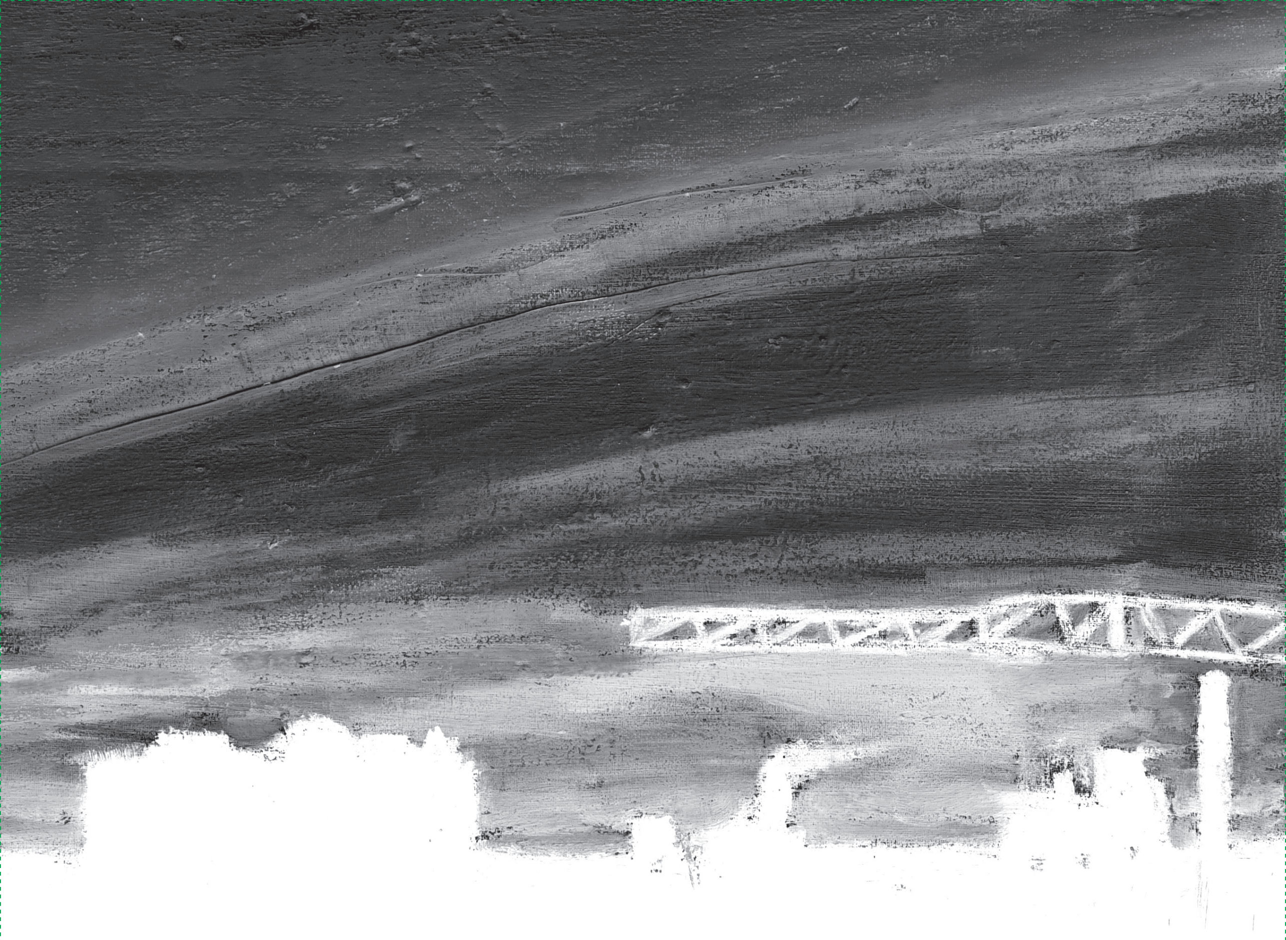

Curriculum Vitae

Sabine van Sleeuwen was born on 4 September 1991 in 's-Hertogenbosch, the Netherlands. She obtained her bachelor's degree in Sociology at Utrecht University in 2013. After finishing her bachelor, she worked as a junior policy advisor at the Netherlands Institute for Human Rights. In 2014, she started the research master Sociology and Social Research at Utrecht University and completed this master in 2016. At the end of her master, she was awarded the Netherlands Organization for Scientific Research (NWO) Talent Grant and in September 2016 she started working as a PhD candidate at the Netherlands Institute for the Study of Crime and Law Enforcement (NSCR) in Amsterdam. Her work has appeared in *Journal of Research in Crime and Delinquency*, *Journal of Quantitative Criminology* and *Crime Science*. Between 2017 and 2020, she taught the courses Statistics I and Statistics II to first-year students of the bachelor Criminology at the VU University Amsterdam. In 2021, she obtained the Teaching Qualification Certificate (BKO) at the VU.

Why do offenders commit crime not only in certain places, but also at certain days and times? Both the theory and related empirical research in environmental criminology have to date remained rather a-temporal, as if the timing of offenders' routine activities and their crimes plays no role. This dissertation improves the original crime pattern theory and proposes a time-specific extension: offenders' spatial knowledge acquired during daily routine activities is not equally applicable to all times of day and week, which influences the locations where they subsequently choose to offend. To test the novel idea of time-varying applicability of offenders' awareness spaces, large-scale police data on repeat offenders of a variety of crime types are combined with the analysis of self-collected data using the Time-specific Activity Space (TAS) survey that was specifically designed for this study. Extending the existing body of research on offenders' spatial decision-making, the results of the four empirical chapters of this dissertation show that studying the temporal criminal decision-making of individual offenders and its practical implications are also of importance.

Sabine van Sleeuwen obtained her master's degree in Sociology and Social Research at Utrecht University. She wrote this dissertation as part of her PhD research project at the Netherlands Institute for the Study of Crime and Law Enforcement (NSCR).