



When Do Offenders Commit Crime? An Analysis of Temporal Consistency in Individual Offending Patterns

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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.

Method 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.

Discussion 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.

Keywords Repeat offenders · Temporal consistency · Hour of day · Hour of week · Monte Carlo permutation

Introduction

Why do offenders commit crime at certain times and places instead of others? Crime pattern theory (Brantingham and 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

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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. 2019; Townsley and Sidebottom 2010; Van Daele and 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 and Malleson 2013), day of the week (e.g., Johnson et al. 2012), time of day (e.g., Haberman and Ratcliffe 2015) or a combination of these temporal cycles (e.g., Andresen and 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 and Wasilchick 2000; Wright and 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.

Theoretical Framework

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 et al. 2013; Ruiter and 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 and 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.

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 and 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 and Wasilchick

2000; Wright and 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 and Wasilchick 2000; Wright and Decker 1994) and levels of guardianship are low (Coupe and 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.

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.

Data and Methods

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 and Van Gaalen 2008; Blom et al. 2005).

Crime Times and Crime Types

Each crime record in the Dutch police data has two time variables, one related to the starting 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 et al. 2018). In this study, only offenses with a maximum of 24-hour difference in start and end time are included, as differences exceeding 24 h 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 starting 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 starting dates and times instead of the ending records, as well as the midpoint between the starting and ending 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 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 Fig. 1, while these are broken down by crime type in Fig. 2.

Table 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	1620	1.06
	Drugs	5254	3.45
	Weapons	3299	2.17
	Other	5312	3.49
Total number of offenses per offender		28,274	100.00^a
	2 offenses	11,830	41.84
	3 offenses	5174	18.30
	4 offenses	2847	10.07
	5 offenses	1824	6.45
	6 offenses	1240	4.39
	7 offenses	901	3.19
	8 offenses	679	2.40
	> 8 offenses	3779	13.37

^aPercentages do not total 100 due to rounding

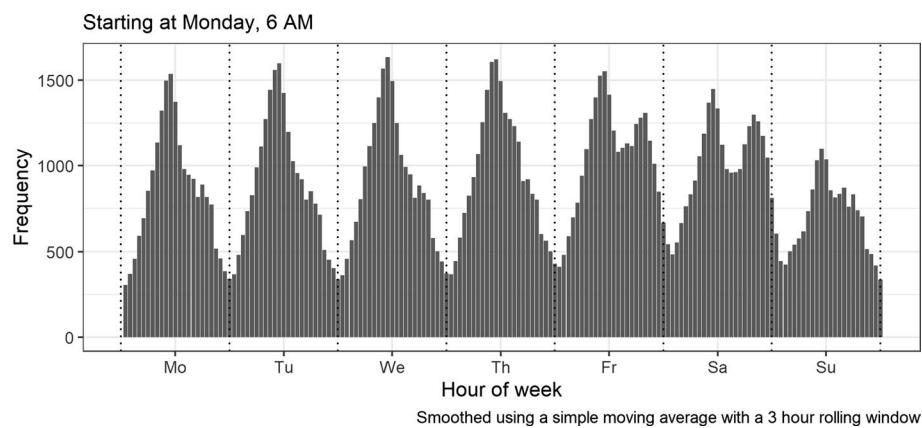
**Fig. 1** Crime frequency during the week ($N=152,180$ offenses committed by 28,274 offenders)

Table 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 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 Fig. 2. For

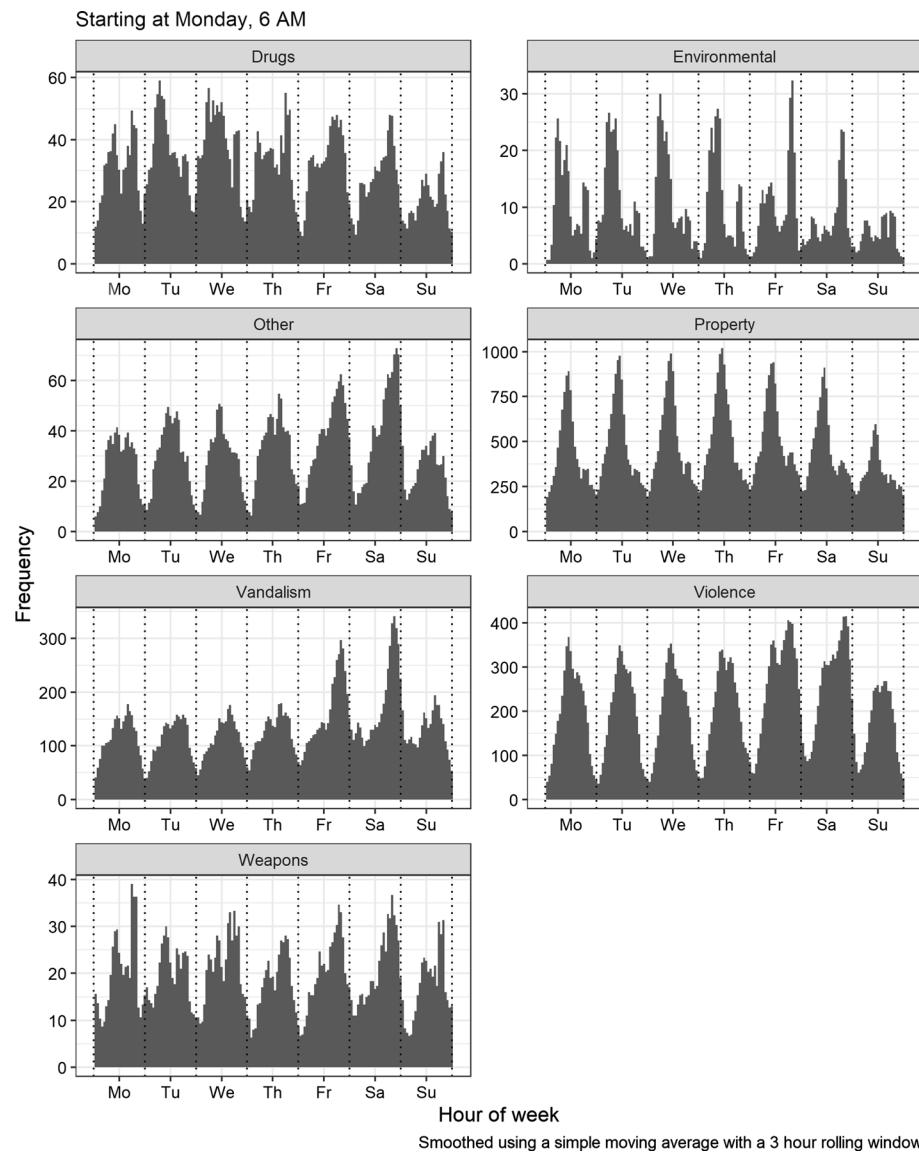


Fig. 2 Crime frequency during the week, by crime type ($N=152,180$ offenses committed by 28,274 offenders)

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.

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 h in total) and hour of week (168 h 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. 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).¹
- (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.² 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 h distance on the 24-hour (daily) clock and a 29 h 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.³
- (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 h distance”) and the sum of the cumulative proportions across all temporal distances is $0 + 0 + 0 + \dots + 1 = 1$. If all offenders commit all crimes at exactly the same hour of day, 100% of crime pairs are found in the first category (“0 h distance”) and the sum of the cumulative proportions is $1 + 1 + 1 + \dots + 1 = 13$. 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,

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

² 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.

³ For hour of day, there are 13 circular temporal distance categories: 0 h, 1 h, 2 h, ..., 12 h. For hour of week, there are 85 circular temporal distance categories: 0 h, 1 h, 2 h, ..., 84 h.

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 $\{-1, 1\}$.⁴ 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).⁵ 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).

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 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 permuted temporal consistencies to assess the likelihood of observing the former. Our hypotheses imply that individual offenders’ crime events should

⁴ 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.

⁵ 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 $\{1/24, 1/12, 1/12, \dots, 1/12, 1/12, 1/24\}$ for the daily cycle, and $\{1/168, 1/84, 1/84, \dots, 1/84, 1/84, 1/168\}$ 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.

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 pseudo-random 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 Fig. 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 permuted data through steps a through f* as described in paragraph 3.3.⁶
- (3) *Repeat steps 1 and 2 9999 times* This leads to 9999 values of temporal consistency that is to be expected given the overall temporal distribution of crime events, one for each of the 9999 permuted datasets. We will refer to the mean of the 9999 temporal consistency values of the permuted 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 et al. 2002). Under the null hypothesis, it is very unlikely that many of these 9999 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 9999 temporal consistency values of the permuted 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 Fig. 4).⁷ In addition, because the TC values are standardized, they are also comparable across temporal scales (here, the daily versus weekly cycle).

Sensitivity Analysis

In the next section, the results are shown for all offenders. However, Table 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 3.2). In additional analyses (not shown here), we observed substantively similar findings when using the starting dates and times instead of

⁶ As only crime pairs that are at most 3 years apart are included in the analysis (see paragraph 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.

⁷ 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 9999 permuted datasets).

the ending records, as well as when using the midpoint between the starting and ending times.

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 Fig. 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 9999 permuted 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 Fig. 3, left). Half of the crime pairs consist of crimes committed with a distance of 0–4 h. 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 Fig. 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 h 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).

For each hour distance, we also display the total range of proportions of crime pairs across the 9999 permuted datasets. For the daily cycle, it is clear that the permuted 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 9999 permuted datasets.

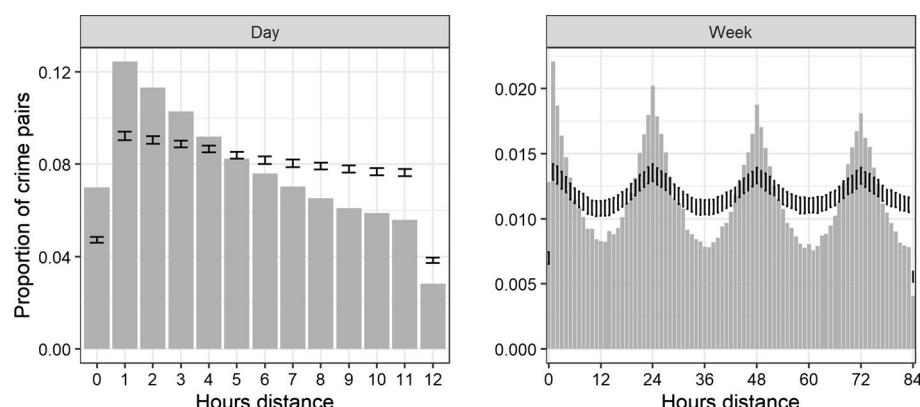


Fig. 3 Proportions of crime pairs by distance in hours of day and hours of week for the observed data (bars), and the total range across the 9999 permuted datasets ($N=28,274$ offenders)

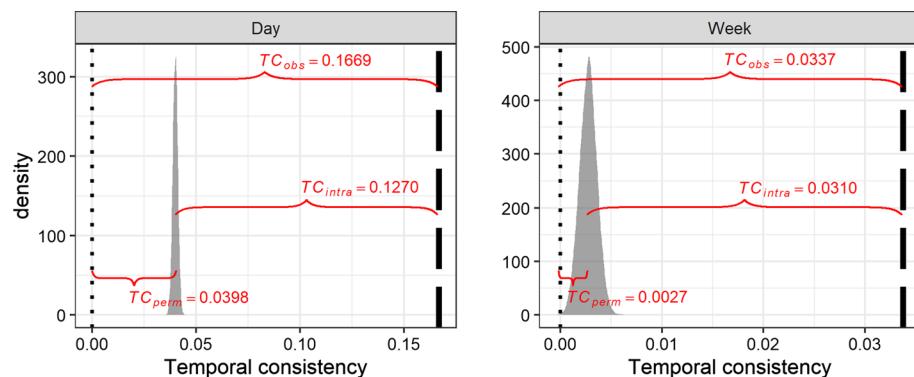


Fig. 4 Visualization of the statistical significance test outcome for Hypothesis 1. The figure shows the hour of day consistency (left) and hour of week consistency (right), and presents key concepts used in the paper. The dotted line at zero indicates random temporal behavior; TC_{obs} =observed temporal 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 9999 permuted datasets (grey distribution); TC_{intra} =the intra-offender temporal consistency (i.e. $TC_{obs} - TC_{perm}$). ($N=28,274$ offenders)

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 4 (left) shows the hour of day consistency observed in the original data (black dashed line), the distribution of temporal consistency values across the 9999 permuted datasets (in grey), and a dotted line at zero for reference indicating random temporal behavior.⁸

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 .1669. The Monte Carlo 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 .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 9999 temporal consistency values: $TC_{intra} = TC_{obs} - TC_{perm} = .1270$. Put differently, of the total observed temporal consistency, about (.1270/.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 ($p=.0001$).

For hour of week, $TC_{obs}=.0337$ (see Fig. 4, right), and TC_{intra} —i.e. the difference between the observed temporal consistency and the mean of the 9999 consistency

⁸ Note: in order to clearly depict the differences between the observed temporal consistency and the 9999 temporal consistency values of the permuted datasets, we use different axes for the hour of day and hour of week analyses.

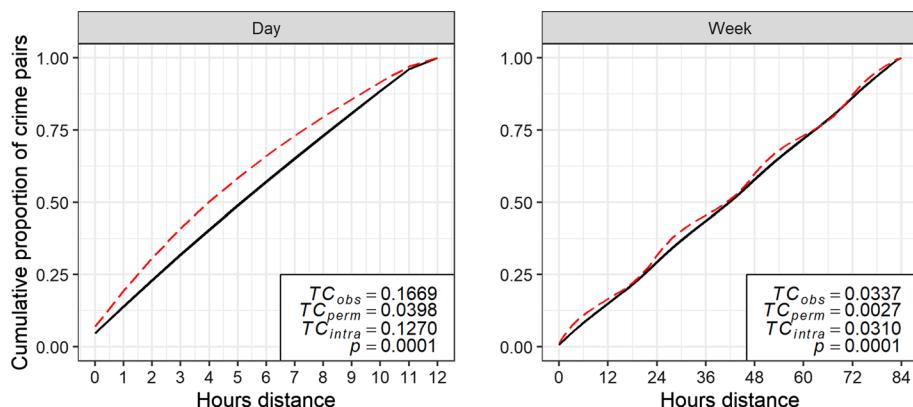


Fig. 5 Cumulative proportions of crime pairs by distance in hours of day and hours of week for the observed data (dashed red), and 200 of the 9999 permuted datasets (solid lines) ($N=28,274$ offenders). Key values are displayed in the bottom-right corner. The p -values indicate whether TC_{obs} is significantly larger than expected in its respective plot (Color figure online)

values of the permuted datasets—equals .031. While the effect is statistically significant ($p=.0001$), $TC_{intra(week)}$ 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, $p=.0001$.⁹ Of the very small weekly temporal consistency that is observed, about 92% is attributable to *intra*-offender behavior.

While Fig. 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 5 presents these observed cumulative proportions for the daily and weekly cycle in dashed red, while the cumulative proportions for 200 permuted datasets are presented as solid lines (for readability, we only draw 200 of the 9999 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.

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 TC_{intra} 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.

⁹ 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.

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 9999 temporal consistency values of the permuted 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 permuted 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

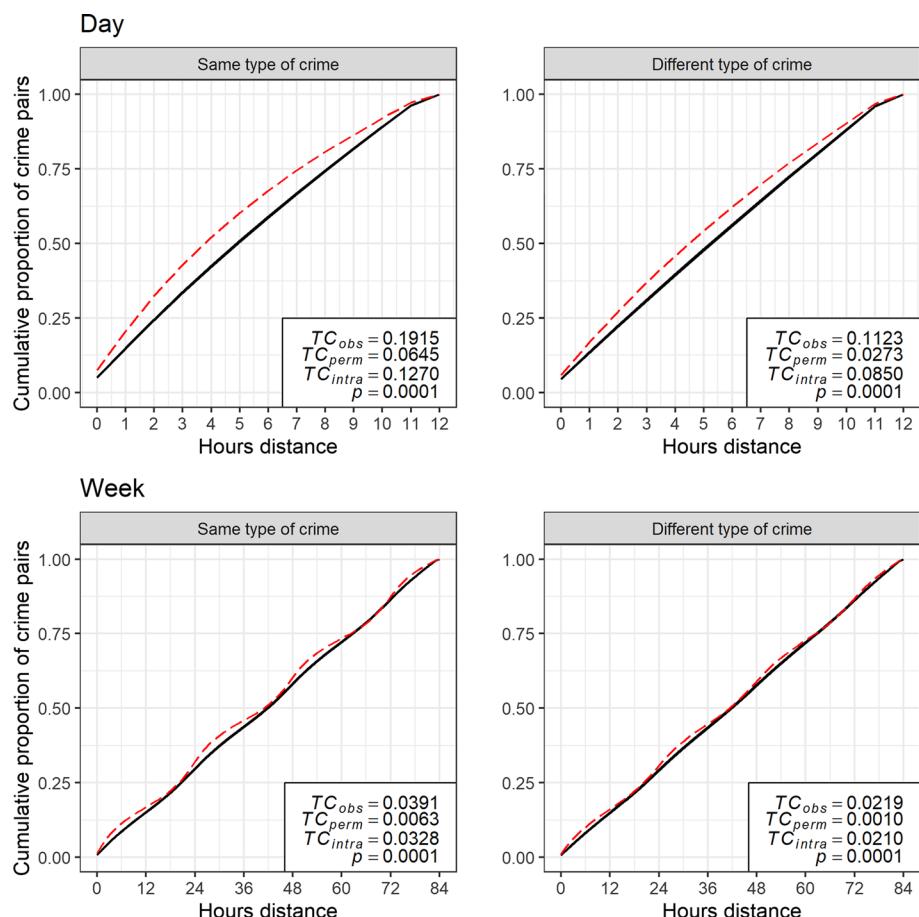


Fig. 6 Cumulative proportions of crime pairs for hour of day (top) and hour of week (bottom), for crime pairs of the same crime type (left) and crime pairs of a different crime type (right). The hypothesis tests the difference between left and right figures ($N=28,274$ offenders)

the cumulative proportions in each of the 9999 permuted 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 $\sum_{i=1}^n (TC_{obs(same\ type)} - TC_{obs(different\ type)}) > (TC_{i,sim(same\ type)} - TC_{i,sim(different\ type)})$ for $i = 1, \dots, 9999$ permuted datasets.

The cumulative proportions for the same type and different type crime pairs are presented in Fig. 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? For both hour of day (Fig. 6, top) and hour of week (Fig. 6, bottom), we can indeed reject the null hypothesis of no effect difference ($p = .0001$). Note, however, that the differences are very small: (.1270 – .0850 =) .042 for hour of day and (.0328 – .0210 =) .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, $p = .0001$). 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.

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 Fig. 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 ($p = .0001$). The effect is also substantively meaningful, with mean expectation of (.1827 – .1103 =) .072. We do not find evidence for more temporal consistency when comparing 31–183 to 184–1096 days between crime events ($p = .9998$). 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 offenders.

As displayed in Fig. 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 ($p = .0001$). The mean size of the difference is (.1057 – .0114 =) .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

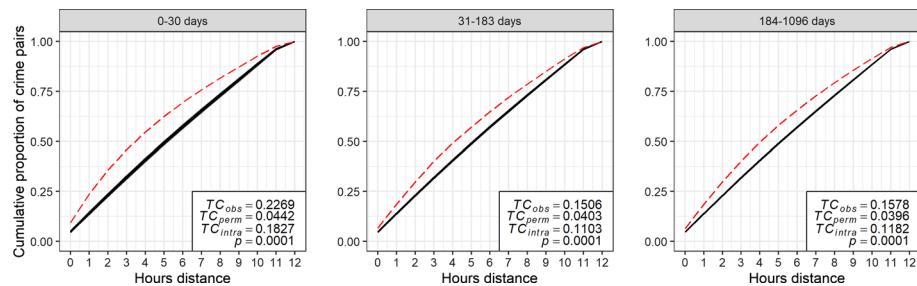


Fig. 7 Cumulative proportions of crime pairs for hour of day within 0–30 days (left), 31–183 days (middle) and 184–1096 days (right). The hypothesis tests the *difference* between left and middle, and middle and right figures ($N=28,274$ offenders)

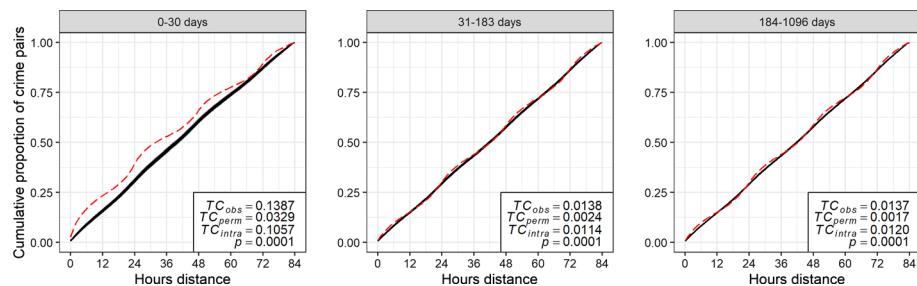


Fig. 8 Cumulative proportions of crime pairs for hour of week within 0–30 days (left), 31–183 days (middle) and 184–1096 days (right). The hypothesis tests the *difference* between left and middle, and middle and right figures ($N=28,274$ offenders)

with 184–1096 days recency ($p=.6041$). 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.

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 2014), 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 et al. (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 overestimated 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 underestimated intra-offender temporal consistency. An estimated 10% of the suspects from the Dutch police system HKS eventually do not get convicted (Besjes and 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 2017). 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 and 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 cyclic time effects (for two exceptions, see Johnson et al. 2007b; Rummens et al. 2017). Hence, future predictive policing methods could benefit from combining cyclic 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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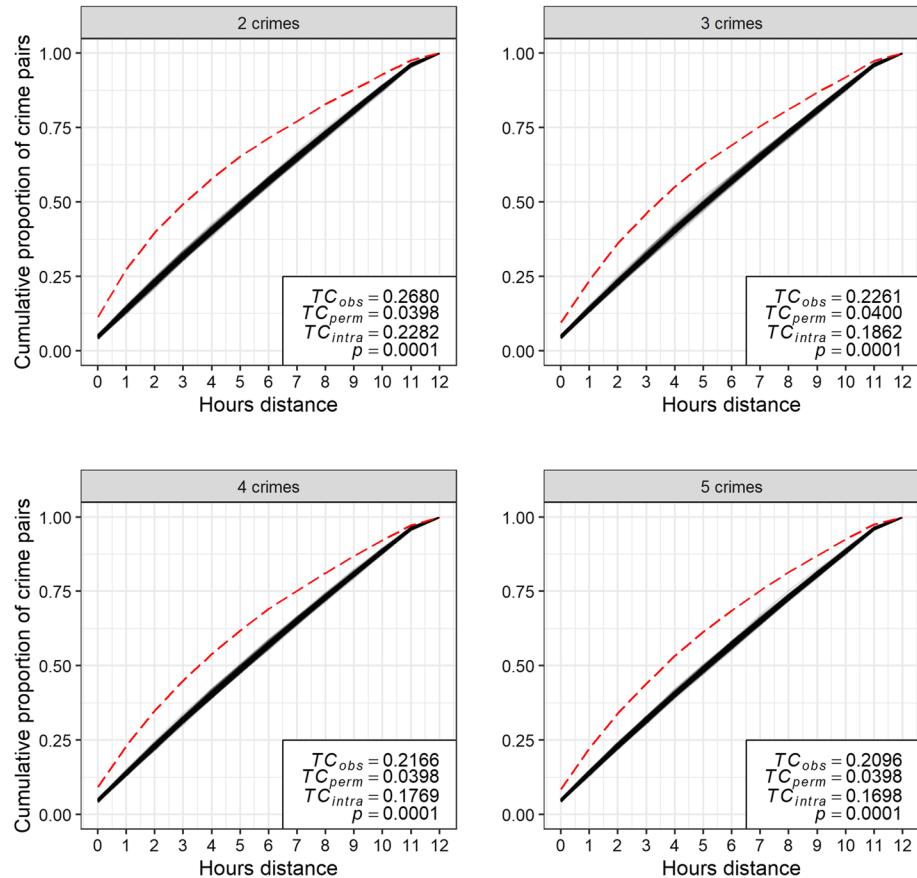
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Appendices

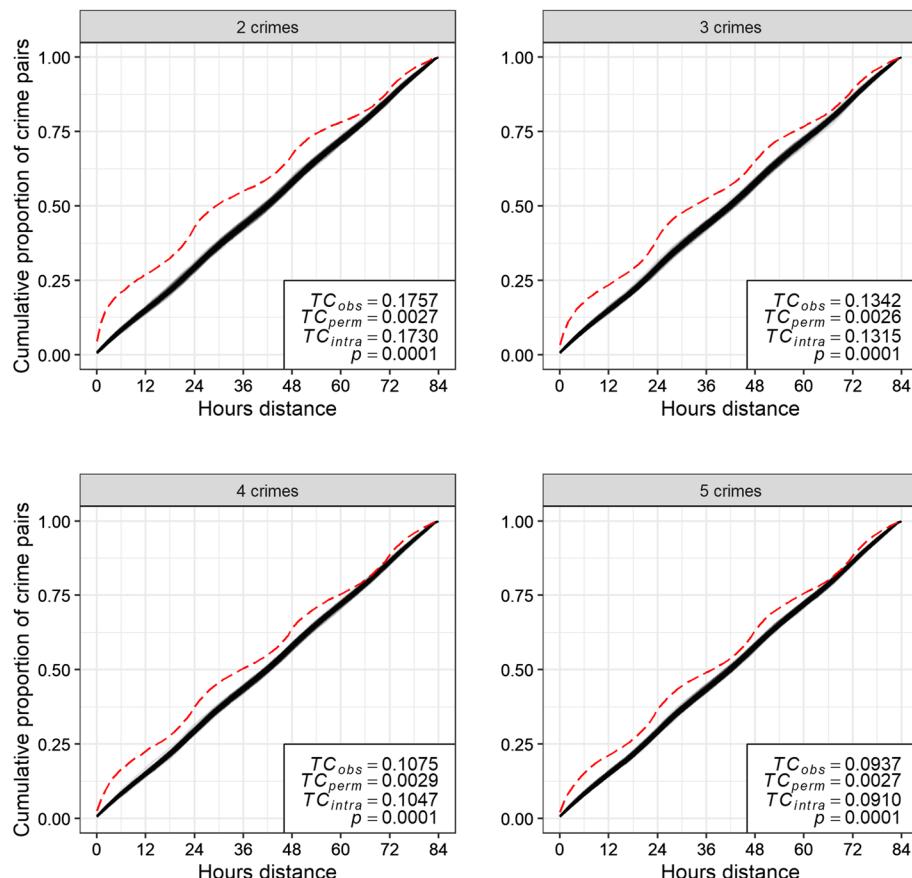
Appendix A1

Hour of day consistency for offenders with 2–5 crimes.



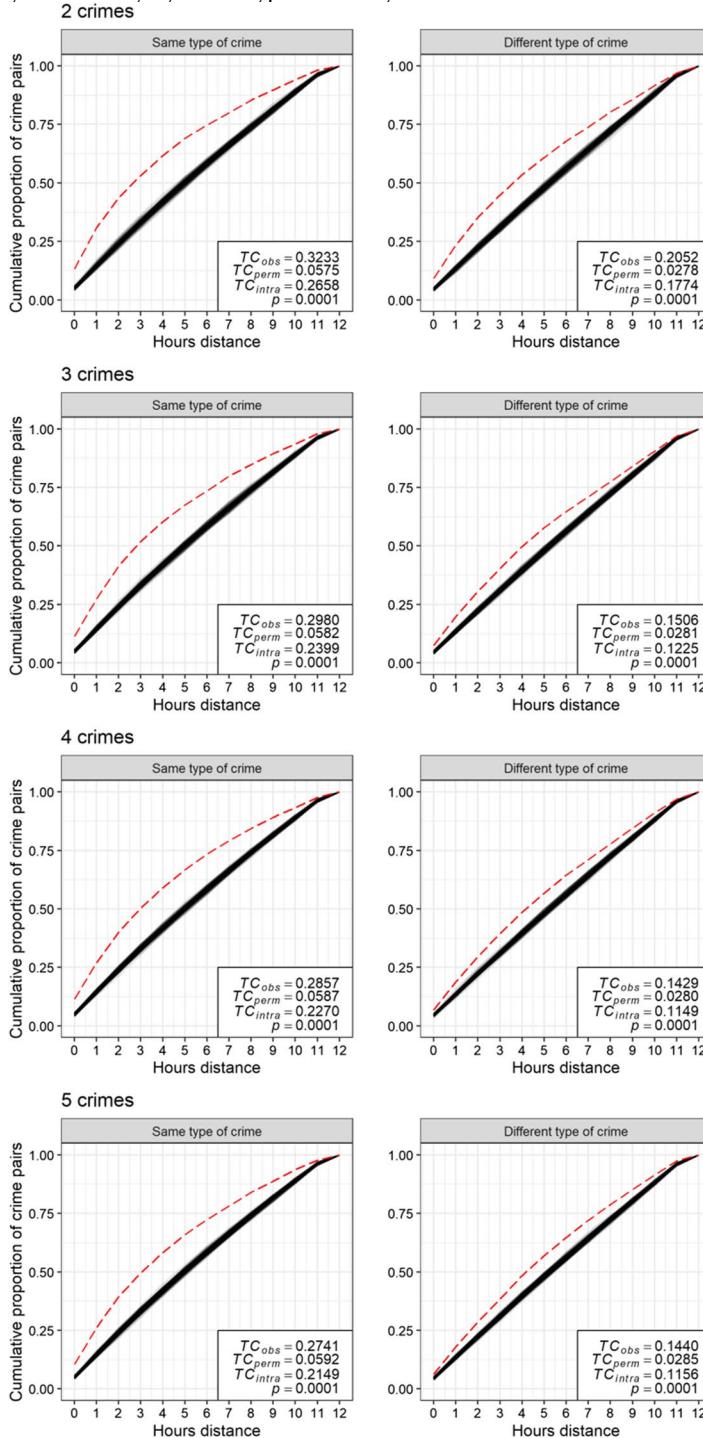
Appendix A2

Hour of week consistency for offenders with 2–5 crimes.



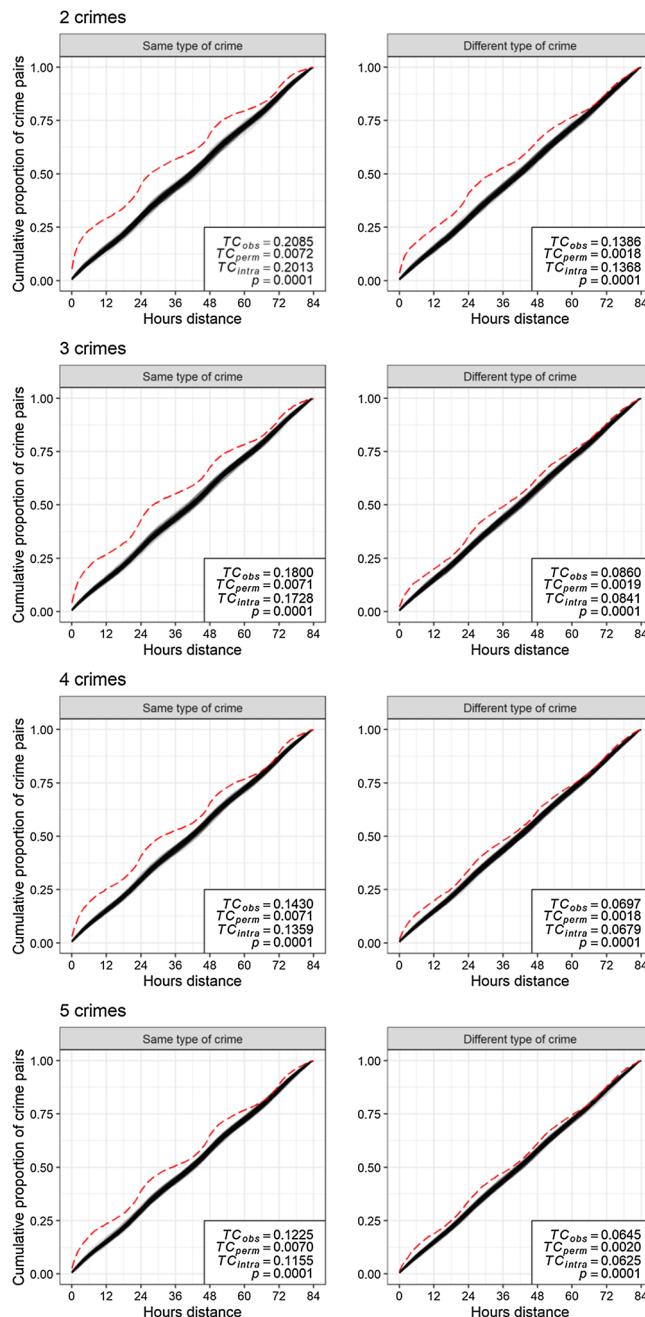
Appendix B1

Hour of day consistency by crime type similarity for offenders with 2–5 crimes.



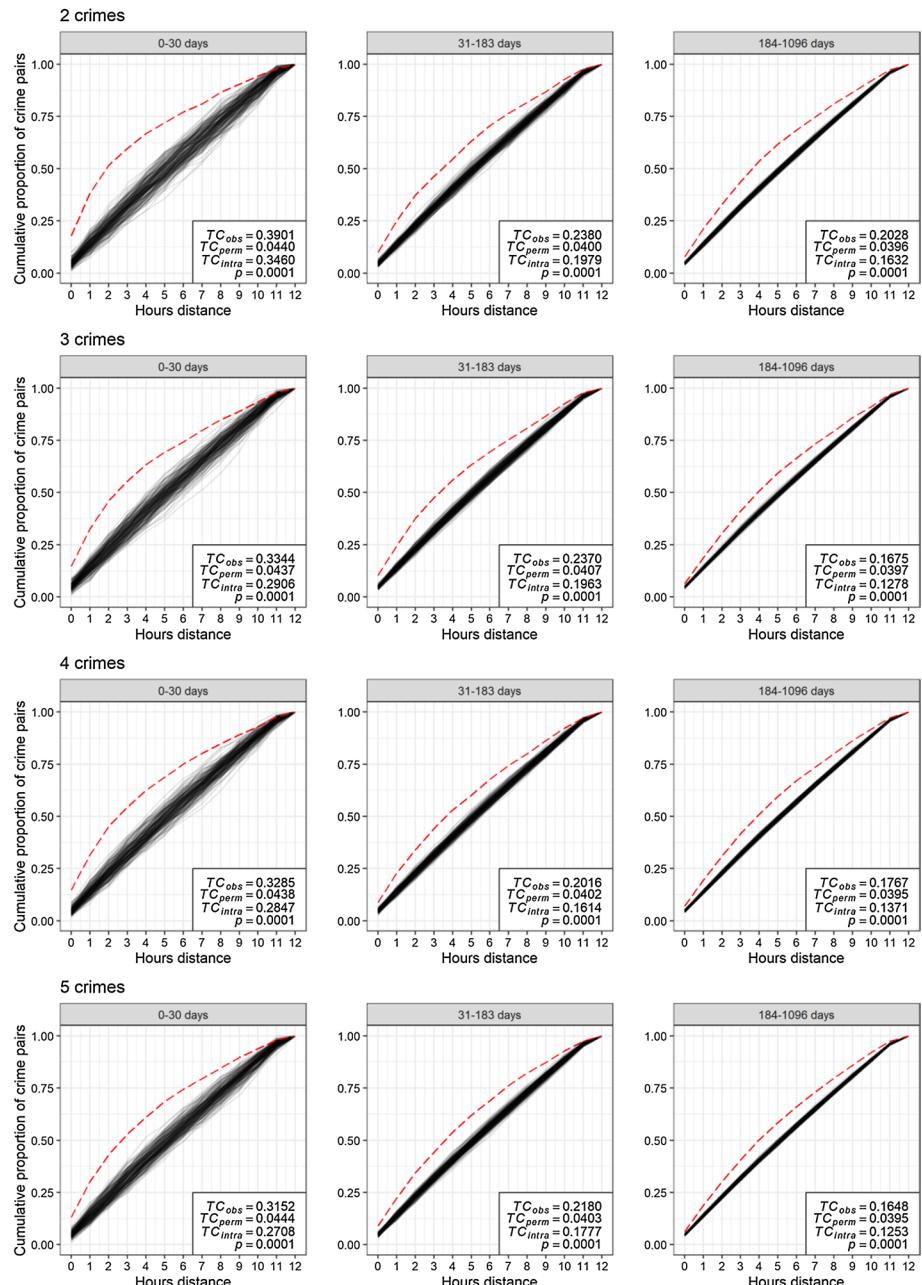
Appendix B2

Hour of week consistency by crime type similarity for offenders with 2–5 crimes.



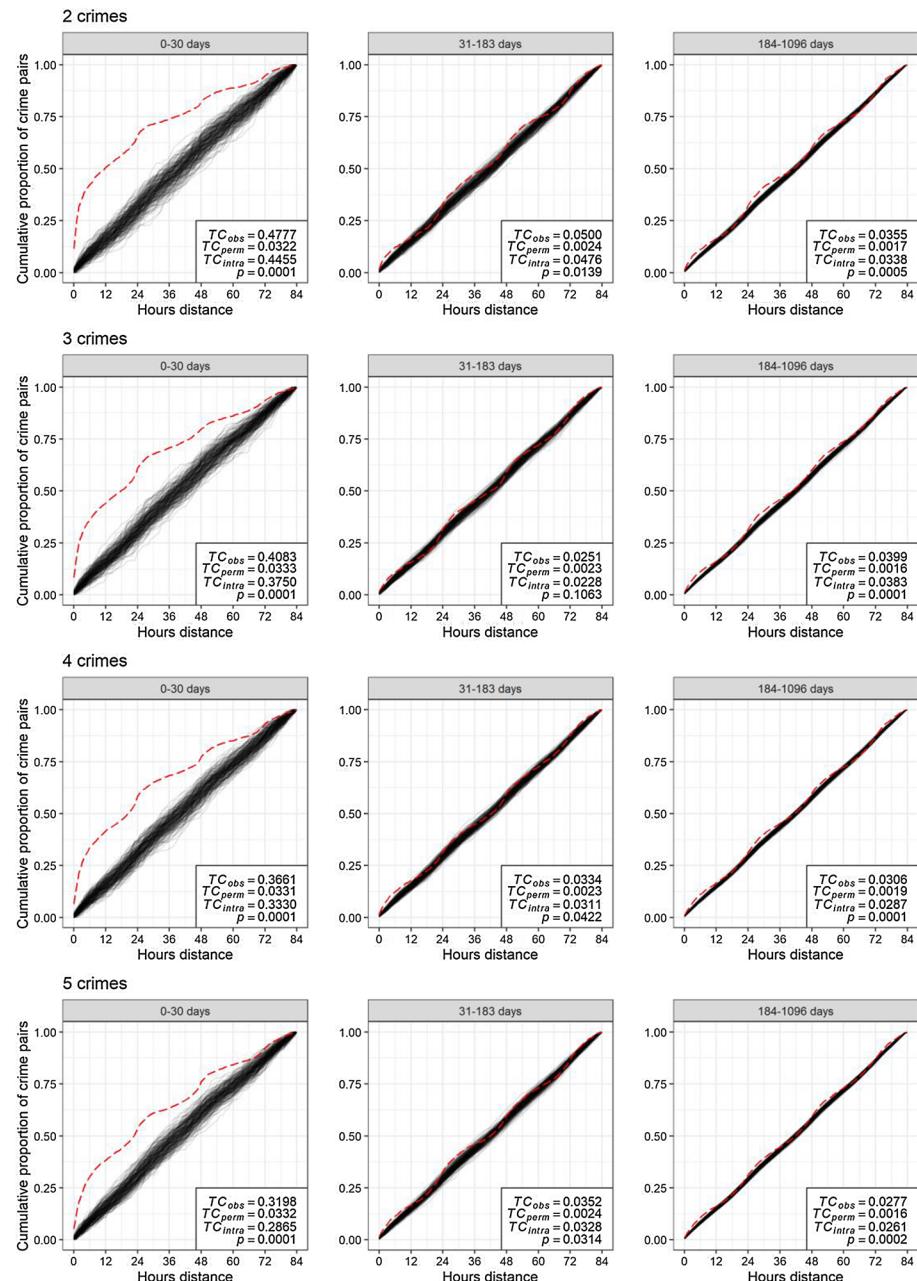
Appendix C1

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.



References

- Andresen MA, Malleson N (2013) Crime seasonality and its variations across space. *Appl Geogr* 43:25–35. <https://doi.org/10.1016/j.apgeog.2013.06.007>
- Andresen MA, Malleson N (2015) Intra-week spatial-temporal patterns of crime. *Crime Sci* 4(1):1–11. <https://doi.org/10.1186/s40163-015-0024-7>
- Barabasi A-L (2005) The origin of bursts and heavy tails in human dynamics. *Nature* 435(7039):207–211
- Bernasco W (2014) Crime journeys: patterns of offender mobility. In: Tonry ME (ed) Oxford handbooks online in criminology and criminal justice. Oxford University Press, Oxford
- Bernasco W, Ruiter S, Bruinsma GJN, Pauwels LJR, Weerman FM (2013) Situational causes of offending: a fixed-effects analysis of space-time budget data. *Criminology* 51(4):895–926. <https://doi.org/10.1111/1745-9125.12023>
- Besjes G, Van Gaalen R (2008) Jong geleerd, fout gedaan? [Early learning, misbehaving?]. *Bevolkingstrends* 2:23–31
- Blom M, Oudhof J, Bijl RV, Bakker BFM (2005) Verdacht van criminaliteit: Allochtonen en autochtonen nader bekeken [A closer look at persons of foreign and Dutch heritage]. WODC, Den Haag
- Bowers KJ, Johnson SD, Pease K (2004) Prospective hot-spotting: the future of crime mapping? *Br J Criminol* 44(5):641–658. <https://doi.org/10.1093/bjc/azh036>
- Brantingham PJ, Brantingham PL (2008) Crime pattern theory. In: Wortley R, Mazerolle L (eds) Environmental criminology and crime analysis. Willian, London, pp 78–93
- Cohen LE, Felson M (1979) Social change and crime rate trends: a routine activity approach. *Am Sociol Rev* 44(4):588–608
- Coupe T, Blake L (2006) Daylight and darkness targeting strategies and the risks of being seen at residential burglaries. *Criminology* 44(2):431–464. <https://doi.org/10.1111/j.1745-9125.2006.00054.x>
- Cromwell PF, Olson JN, Avary DAW (1991) Breaking and entering: an ethnographic analysis of burglary. Sage Publications, Newbury Park
- Gonzalez MC, Hidalgo CA, Barabasi A-L (2008) Understanding individual human mobility patterns. *Nature* 453(7196):779–782. <https://doi.org/10.1038/nature06958>
- Haberman CP, Ratcliffe JH (2015) Testing for temporally differentiated relationships among potentially criminogenic places and census block street robbery counts. *Criminology* 53(3):457–483. <https://doi.org/10.1111/1745-9125.12076>
- Hägerstrand T (1970) What about people in regional science? *Pap Region Sci* 24(1):7–24. <https://doi.org/10.1007/BF01936872>
- Johnson SD, Bernasco W, Bowers KJ, Elffers H, Ratcliffe J, Rengert G, Townsley M (2007a) Space-time patterns of risk: a cross national assessment of residential burglary victimization. *J Quant Criminol* 23(3):201–219. <https://doi.org/10.1007/s10940-007-9025-3>
- Johnson SD, Birks DJ, McLaughlin L, Bowers KJ, Pease K (2007b) Prospective crime mapping in operational context. Home Office, London
- Johnson SD, Summers L, Pease K (2009) Offender as forager? A direct test of the boost account of victimization. *J Quant Criminol* 25(2):181–200. <https://doi.org/10.1007/s10940-008-9060-8>
- Johnson SD, Bowers KJ, Pease K (2012) Towards the modest predictability of daily burglary counts. *Policing* 6(2):167–176. <https://doi.org/10.1093/police/pas013>
- Lammers M (2014) Are arrested and non-arrested serial offenders different? A test of spatial offending patterns using DNA found at crime scenes. *J Res Crime Delinq* 51(2):143–167. <https://doi.org/10.1177/0022427813504097>
- Lammers M (2017) Co-offenders' crime location choice: Do co-offending groups commit crimes in their shared awareness space? *Br J Criminol* 58(65):1193–1211. <https://doi.org/10.1093/bjc/azx069>
- Lammers M, Bernasco W, Elffers H (2012) How long do offenders escape arrest? Using DNA traces to analyse when serial offenders are caught. *J Investig Psychol Offender Profiling* 9(1):13–29
- Lammers M, Menting B, Ruiter S, Bernasco W (2015) Biting once twice: the influence of prior on subsequent crime location choice. *Criminology* 53(3):309–329. <https://doi.org/10.1111/1745-9125.12071>
- Lundrigan S, Canter D (2001) A multivariate analysis of serial murderers' disposal site location choice. *J Environ Psychol* 21(4):423–432. <https://doi.org/10.1006/jenvp.2001.0231>
- Markson L, Woodhams J, Bond JW (2010) Linking serial residential burglary: comparing the utility of modus operandi behaviours, geographical proximity, and temporal proximity. *J Investig Psychol Offender Profiling* 7(2):91–107. <https://doi.org/10.1002/jip.120>
- Menting B, Lammers M, Ruiter S, Bernasco W (2019) The influence of activity space and visiting frequency on crime location choice: findings from an online self-report survey. *Br J Criminol*. <https://doi.org/10.1093/bjc/azz044>

- Miller HJ (2005) A measurement theory for time geography. *Geogr Anal* 37(1):17–45. <https://doi.org/10.1111/j.1538-4632.2005.00575.x>
- Mohler GO, Short MB, Malinowski S, Johnson D, Tita GE, Bertozzi AL, Brantingham PJ (2015) Randomized controlled field trials of predictive policing. *J Am Stat Assoc* 110(512):1399–1411. <https://doi.org/10.1080/01621459.2015.1077710>
- North BV, Curtis D, Sham PC (2002) A note on the calculation of empirical P values from Monte Carlo procedures. *Am J Hum Genet* 71(2):439–441. <https://doi.org/10.1086/341527>
- Pappalardo L, Simini F, Rinzivillo S, Pedreschi D, Giannotti F, Barabási A-L (2015) Returners and explorers dichotomy in human mobility. *Nat Commun* 6:1–8. <https://doi.org/10.1038/ncomms9166>
- Ratcliffe JH (2002) Aoristic signatures and the spatio-temporal analysis of high volume crime patterns. *J Quant Criminol* 18(1):23–43. <https://doi.org/10.1023/A:1013240828824>
- Ratcliffe JH (2006) A temporal constraint theory to explain opportunity-based spatial offending patterns. *J Res Crime Delinq* 43(3):261–291. <https://doi.org/10.1177/0022427806286566>
- Rengert GF, Wasilchick J (2000) Suburban burglary: a tale of two suburbs. Charles C. Thomas, Springfield
- Ruiter S, Bernasco W (2018) Is travel actually risky? A study of situational causes of victimization. *Crime Sci.* <https://doi.org/10.1186/s40163-018-0084-6>
- Rummens A, Hardwicks W, Pauwels L (2017) The use of predictive analysis in spatiotemporal crime forecasting: building and testing a model in an urban context. *Appl Geogr* 86:255–261. <https://doi.org/10.1016/j.apgeog.2017.06.011>
- Song C, Qu Z, Blumm N, Barabási A-L (2010) Limits of predictability in human mobility. *Science* 327(5968):1018–1021. <https://doi.org/10.1126/science.1177170>
- Statistics Netherlands (2014) Toelichting bij de Standaardclassificatie Misdrijven CBS 1993 [Explanation of the Standard Classification Crimes CBS 1993]. <https://www.cbs.nl/nl-nl/onze-diensten/methoden/classificaties/misdrijven/toelichting-bij-de-standaardclassificatie-misdrijven-cbs-1993>
- Summers L, Johnson SD, Rengert GF (2010) The use of maps in offender interviewing. In: Bernasco W (ed) Offenders on offending: learning about crime from criminals. Willan Publishing, Cullompton, pp 246–272
- Tonkin M, Woodhams J, Bull R, Bond JW, Palmer EJ (2011) Linking different types of crime using geographical and temporal proximity. *Crim Justice Behav* 38(11):1069–1088. <https://doi.org/10.1177/0093854811418599>
- Townsley M, Sidebottom A (2010) All offenders are equal, but some are more equal than others: variation in journeys to crime between offenders. *Criminology* 48(3):897–917. <https://doi.org/10.1111/j.1745-9125.2010.00205.x>
- Van Daele S, Bernasco W (2012) Exploring directional consistency in offending: the case of residential burglary in The Hague. *J Investig Psychol Offender Profiling* 9(2):135–148. <https://doi.org/10.1002/jip.1358>
- Van Sleeuwen SEM, Ruiter S, Menting B (2018) A time for a crime: temporal aspects of repeat offenders' crime location choices. *J Res Crime Delinq* 55(4):538–568. <https://doi.org/10.1177/0022427818766395>
- Wright RT, Decker SH (1994) Burglars on the job: streetlife and residential breakins. Northeastern University Press, Boston

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