



Location Choice of Snatching Offenders in Chennai City

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Abstract

Objectives We aim to test the applicability of crime pattern theory in an Indian urban context by assessing the effects of offender residence, prior offending locations and presence of crime generators and crime attractors on where offenders commit offences.

Methods The data comprise 1573 police-recorded snatching offenses committed by 1152 identified offenders across the 201 wards of Chennai City. We used discrete crime location choice models to establish the choice criteria that snatching offenders use when they decide where to offend. Data on the locations retail businesses, religious and transportation facilities were collected using Google location services.

Results The results confirm that snatching offenders prefer to target locations close to their residence and that they prefer to re-offend at or near their prior offending locations. The findings also demonstrate that some but not all crime attractors and generators influence the location choice of snatching offenders.

Conclusions By replicating in an Indian context previously published crime location choice findings, our findings support the generality of crime pattern theory. We discuss limitations and make suggestions for future investigations.

Keywords Snatching · Crime location choice · Repeat offending · Crime generators · Crime pattern theory · India

Introduction

Over the past two decades, crime location choice has emerged as an influential line of research in the geography of crime and environmental criminology (Ruiter 2017). The key question that crime location choice studies address, is why offenders prefer some places over other places for committing crime. The approach is rooted in rational choice theory, in particular the assumption that offenders use some form of cost–benefit optimization when

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they decide where to commit crime. It is informed by opportunity theories, which state that offenders commit crimes where crime opportunity is abundant and risk of apprehension is low. The approach is also informed by the geography of crime, which emphasizes that criminal opportunities can only be exploited by offenders who are aware of them. The primary purpose of crime location choice studies is to widen and deepen our knowledge of offender decision making. The results may be applied in criminal investigations, where they might help the police to prioritize the most likely suspects of unsolved crimes.

The present study contributes to this line of research by investigating the location choices of snatching offenders in Chennai City, India. Snatch theft involves stealing valuables from a victim with or without force (Curran et al. 2005; Patel 2016). In snatch thefts, an offender spots and snatches items from the victim and runs or drives away (Monk et al. 2010). The offense may, but need not, include the use of force and weapons, and it thus subsumes theft from the person, mugging and street robbery.

Our main contributions to the extant literature in quantitative criminology are three-fold. The first applies to cultural context. A limitation of the extant literature is that almost all crime location choice studies have been conducted in western countries, in particular the United States, Australia, the United Kingdom, the Netherlands and Belgium. The two only exceptions, one on snatching offenses and one on robbery, are from China (Long et al. 2018; Song et al. 2019). Therefore, little evidence is available on whether the methods developed in western countries and the findings they produce can be generalized to countries with different economic, social and cultural characteristics, including India. This is particularly relevant because the foundational theories of crime location choice have also been developed in western cultures. In the application of the crime location choice approach to property crime in India, it is important to reconsider empirical indicators useful in the western context, and to select indicators that reflect key theoretical concepts in the Indian cultural context. For example, marriage halls, temples, mosques and churches play a much larger social role in the daily routines of most Indians than in those of most westerners. The presence of these facilities motivates people to wear valuable jewelry and clothing ornaments in outdoor settings. Because snatchers could feed on this phenomenon, these facilities are included in the present study. A couple of Indian studies (Jaishankar et al. 2009; Sivamurthy 1989; Sivasankar and Sivamurthy 2016) explored the geography of crime, but these studies used aggregated crime data and focused on description and crime mapping rather than use individual data and focus on theory testing and explanation. Thus, the present study pioneers the theory and methodology of crime location choice in the Indian context.

Second, whereas other crime location choice studies have typically collected or purchased data on indicators of criminal opportunity either from governmental agencies or commercial data warehouses, the present study exploits rich and detailed data made accessible through Google Earth for collecting detailed information on the locations of large numbers of facilities (e.g. transit hubs, retail stores, schools, and entertainment facilities) that are visited daily by the people of Chennai city. Our utilization of these data demonstrates how issues like facility duplication and facility function mixing can be addressed. It may be timely because large-scale spatially referenced information from location service providers such as Google (or Baidu in China) is becoming increasingly important in the quantitative spatial analysis of crime.

Third, our study contributes to a recently emerged line of research on location choice in repeat offending, and applies it to snatching. Bernasco et al. (2015) found that when committing crimes, serial offenders tend to commit subsequent crimes in and near locations of their previous crimes. They argue that the initial crime increases the offender's

awareness of the location and the opportunities and challenges that it presents. Hence, the initial crime increases the likelihood that the offender's next crime will be committed near the first. The present study adds to this area of research by readdressing this hypothesis with snatching data from Chennai.

Review of Literature

Prior studies suggest that crime location choices are affected by the distance from the offenders' homes, by offenders' incentives of returning to locations of their prior crimes, and by the presence of crime generators and crime attractors. The present section provides a brief overview of these concepts and summarizes the main empirical findings reported in the extant literature.

Distance

The distance travelled by offenders to the location of the crime they committed is often referred as the *journey to crime*. In practice, however, the journey itself is rarely recorded, and most studies analyze the distance between the offender's home and the crime site. The home-crime distance is subject to a distance decay pattern: most distances are short and the number of crimes declines with the distance from the offender's home. The presumed explanation for this pattern is inspired by rational choice theory. It states that offenders prefer traveling shorter distances over traveling longer distances, because it requires less time and transportation costs (Rengert and Wasilchick 1985; Wiles and Costello 2000). This preference for near locations is not absolute, though, because the costs of longer travel might be compensated if longer crime trips are expected to yield greater rewards (Xiao et al. 2018).

Crime pattern theory suggests that offenders mostly restrict their offending to places that they are familiar with through their daily routines (Brantingham et al. 2017). Because familiar areas tend to be those that are closer to the offenders' residences (Bernasco and Nieuwbeerta 2005; Hockey 2016; Nee et al. 2019; Townsley et al. 2015), familiarity provides an alternative or additional explanation for the distance decay finding. Because of the ubiquity of the finding that offenders prefer shorter over longer distances (Ruiter 2017), and because we have no reasons to expect that Chennai based snatchers would stand out, we formulate the *distance hypothesis*:

The closer a location is to the home of the snatcher, the more likely the snatcher is to select it for snatching.

Repeat and Near Repeat Offending

For various types of crime, empirical studies have demonstrated that the risk of criminal victimization is elevated in the wake of a previous victimization, not only for the initial target (repeat victimization), but also for nearby targets (near repeat victimization) (Johnson et al. 2007; Ratcliffe and Rengert 2008). This finding may appear surprising if we assume that victims are motivated to be vigilant shortly after being victimized, and that the same holds true for those who are in the victim's immediate environment. It has been argued that the explanation may be based on the offender's motivation to return to previous offending locations to

exploit what they learned about a location during their the previous offence (Glasner et al. 2018). Indeed, empirical studies confirm that repeat and near repeat burglaries are often committed by the same offenders who committed the initial burglary (Bernasco 2008; Everson and Pease 2001; Johnson et al. 2009). Furthermore, some crime location studies have confirmed that offenders tend to reoffend in and near locations they previously targeted (Bernasco et al. 2015; Lammers et al. 2015; Long et al. 2018). The present research attempt to replicate this finding for snatching offenders in Chennai, and tests the *repeat offending hypothesis*:

If a location is previously targeted by the snatcher, the snatcher is more likely to select it on the next snatching offense.

Crime Generators and Crime Attractors

Crime generators have been defined as locations where many people converge for reasons unrelated to criminal motivation (Brantingham and Brantingham 1995), such as shopping malls, parks, transport hubs, and markets. Larger crowds imply larger numbers of potential offenders and larger numbers of potential victims of personal crimes, and therefore more criminal opportunities (Chen et al. 2017; Townsley et al. 2016). *Crime attractors* are locations that attract motivated intending offenders because they provide specific criminal opportunities (Brantingham and Brantingham 1995). There is considerable overlap between crime generators and crime attractors. Because they cannot be reliably distinguished without knowledge of offender motivation and premeditation, there are often treated as a single category ‘crime generators and attractors’. It is expected that offenders are more likely to offend at or near crime generators and attractors because these locations provide more criminal opportunities.

In the context of snatch theft, crime generators and attractors increase the number of people present who carry items that are attractive to offenders, in particular items that are concealable (easy to hide in pocket or bag), removable (not fixed, or easily detached), available (widely used), valuable (expensive), enjoyable (consumable if not valuable and disposable), and disposable (easy to sell), six attributes that are summarized in the acronym CRAVED (R. V. Clarke 1999). Hence, the present study attempts to test the influence of crime generators and attractors, many of which bring together many people with CRAVED items, on the location choices of snatching offenders. Cash money is the prime example of a CRAVED item. Smartphones, laptops and other electronic devices are also CRAVED.

In Indian culture, gold in the form of jewelry and clothing ornaments plays an important role in social life, and locations where many people wear jewelry (e.g., marriage halls, temples and other places of worship) may attract snatchers. Other facilities where many people concentrate, such as transit stations, retail centers, and educational institutions, are also expected to attract snatching offenders because of the presence of many potential victims, some of whom carry CRAVED items. Thus, we formulate the generic *crime generators and attractors hypothesis*:

The larger the number of facilities (of any given facility type) in a location, the more likely a snatcher it is to select it for a snatching offense.

Data and Methods

The study area for the present research is the Greater Chennai City Corporation, a metropolitan area with a population of over 6.6 million during the latest census in 2011. It consists of 201 wards with an average surface area of 2.18 km² (quartiles 0.97, 1.61 and 2.53) and an average population of 33,195 (quartiles 21,451, 36,560 and 43,622). In terms of surface area, the wards are similar in size to neighborhoods or census tracts that have been used in crime location studies elsewhere (i.e., Long et al. 2018; Townsley et al. 2015), but due to the high population density in Chennai, the population sizes of wards are larger than those in most other studies.

Crime Data

We investigate all detected snatching offenses from August 2010 to July 2017 committed in the study area committed by offenders who lived in the study area. The offense data were obtained from the State Crime Records Bureau, Tamil Nadu, India. They include the time, date, and location of all recorded and detected snatching offenses, and they also contain the age, gender and address of the offender. The data consist of 1573 snatching offenses committed by 1152 offenders. Based on all snatching offenses reported to the police, the detection rate of snatching offenses in Chennai City is estimated to be approximately 35 percent. During a period of 7 years, 1573 cleared snatching offenses in a city of 6.6 million is a very low number in comparison to the numbers of similar offenses reported in western countries. Although India has no national crime victimization survey and does not participate in the International Crime Victimization Survey (Ansari et al. 2015) it has been estimated that in Indian cities only between 6 and 8 percent of the victims of theft report to the police (Durani et al. 2017), so that police recorded thefts grossly underestimate the real numbers of thefts. In many countries it has been found that whether victims report to the police depends on attributes of the victim, the offender and the offense (Goudriaan et al. 2006), and India is probably no exception. Although some research suggests that the high rate of underreporting in India might not bias comparisons between geographical areas (Prasad 2013), the high level of underreporting at least potentially jeopardizes generalizations, and thus forces us to be careful in drawing conclusions. We further address the issue in the final section.

In the data, the location of a snatching offense is marked with a nearby address. For example, a snatching on the parking near a supermarket would be recorded at the address of the supermarket. The exact locations and the recorded locations are therefore approximate, and might diverge by 100 or occasionally 200 m. The addresses of the offenders are complete addresses. The addresses of the offense locations and of the offenders' residences were both geocoded using Google Earth.

Based on the recorded dates of the crimes, for each snatching offense the number of prior snatching offenses committed by the same offender was determined per ward. Thus, for each snatching offense it was recorded in which wards each of the offender's previous snatching offenses (if any) had been committed.

Table 1 presents descriptive information about the 1573 analyzed snatching offenses, including the age and gender of the offender, and whether it was committed in the offender's own ward of residence.

Table 1 Offender age, gender, and local offense indicator (N= 1573 offenses)

	Count	%
<i>Age</i>		
13–18	96	6.10
19–25	892	56.71
26–30	319	20.28
31–35	140	8.90
36–40	65	4.13
41 or older	61	3.88
<i>Gender</i>		
Female	6	0.38
Male	1567	99.62
<i>Crime in home ward</i>		
False	1472	93.58
True	101	6.42

Table 2 Number of offenses recorded per offender

No of crimes	Frequency	Offenses
1	922	922
2	139	278
3	48	144
4	25	100
5	4	20
6	4	24
7	6	42
8	1	8
9	2	18
17	1	17
Total	1152	1573

Most offenders are young adults in the 19–25 age range, and few of them are younger than 19 or older than 35. Snatching is an almost entirely male activity, with only 6 female offenders being charged for the offense over an eight-year period. Approximately 6 percent of the offenses were committed within the offender's own ward of residence.

Table 2 documents how many of the 1573 offenses involved how many of the 1152 offenders. For the large majority (80 percent) of the offenders only a single snatching offense was recorded during the eight-year study period in Chennai City. The number of snatching offenses for the other 20 percent ranged from 2–17 offenses, with the majority having 2 (20 percent), 3 (4 percent) or 4 (2 percent) recorded snatching offenses. With respect to repeat offending, this implies that 421 of the 1573 offences (27 percent) were repeat offenses committed by the same offender.

For every detected snatching incident, the distance was calculated between the home of the offender and the centroids of each of the 201 wards. Based on these distances, Fig. 1 shows the distribution of the home-crime distance, which reveals the typical positively skewed distance decay pattern.

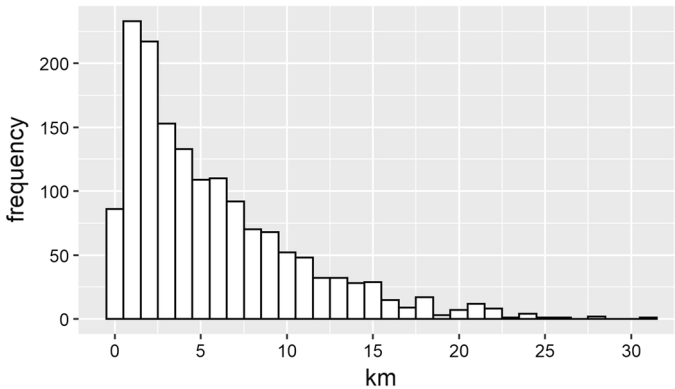


Fig. 1 Distance between offender's home and snatching location (N = 1573)

Crime Generators and Attractors

To measure geographic variations in criminal opportunity, and based on the extant Western and non-Western literature on crime generators and attractors (Bernasco and Block 2011; Haberman and Ratcliffe 2015; Long et al. 2018; Song et al. 2019), we searched for and collected information on the locations of presumed crime generators and attractors. Based on advertised or well-known functions and services of 'points of interest' or 'facilities', we took into consideration whether a facility is likely to attract many people (its crime generator function) and whether it is likely to attract people that are suitable snatching victims because they carry CRAVED items (its crime attractor function).

Transport hubs are a potentially important category of crime generators. Chennai is a densely populated city. It has a huge transport infrastructure, and 75 percent of Chennai residents use public transport (OLA Mobility Institute 2018). We distinguish between *train stations* and *bus stops*. Train stations include MRTS stations, metro stations, and suburban train stations. Bus stops include bus stops and bus depots. People in transit may be suitable snatching victims if they wear or carry CRAVED items and are distracted.

Schools and colleges and other *educational institutions* also serve as meeting points for a large part of the population, in particular young people. Schools and colleges are distinguished from other educational institutions because schools and colleges are typically large-scale but fewer in number than other educational institutions, which tend to be much larger in number but much smaller in scale. For adults, *government offices* (attracting both workers and visitors) were included as potentially relevant locations where people meet many others.

As everywhere else, in Chennai retail facilities that sell tangible items are widely available and attract many customers. They include *supermarkets*, *textile stores* (including clothing and fabric shops), *vegetable markets*, and *general stores*. Their environs provide snatching opportunities because they bring together large volumes of people in a single place, although the potential victims do not necessarily carry CRAVED items. The same holds true for facilities that provide services for *personal care*, such as barbers shops, beauty parlors, saloons and spas, and for *restaurants*. Facilities that provide medical services include hospitals, but also include a wide variety of facilities that provide *medical services* or sell medicines.

Gold plays a major role in the culture of India. According to the World Gold Council, a market development organization and data repository for the gold industry, India is one of the largest markets for gold. It states that gold has a central role in the country's culture and plays a fundamental part in many religious rituals and personal life events, in particular weddings, which alone generate approximately 50 percent of the annual gold demand of India (World Gold Council n.d.). Most gold is worn during festivals, rituals and while going to the temple. Besides festivals and special occasions, gold is also part of the daily clothing and accessories of Indians. For this reason, the environs of *temples*, so-called '*marriage halls*' and *jewelry shops* can be attractive locations for snatchers. The same argument applies to *mosques* and *churches*, places of worship for Muslims and Christians, two large religious minorities in Chennai.

Google's location information, as made accessible through the Google Maps/Earth software, was used to establish the coordinates, names and categories of facilities expected to function as crime generators and attractors. Google Earth has been shown to provide reliable, complete and cost-effective data on many phenomena (P. Clarke et al. 2010; Kelly et al. 2012; Taylor and Lovell 2012). Therefore, we used Google Earth to access Google location services data on all facilities in Chennai.

Based on the literature and taking into consideration particular features typical of India and Chennai city, 35 keywords were used as search terms in Google Earth Pro to get details of 23 types of facilities. For example, textile stores were searched using keywords 'textiles', 'clothing' and 'fashion'. To ensure complete coverage of the study area, the geographic selection was defined as 'near Chennai'. Appendix 1 provides an overview of facility categories and keywords used in the search process. In addition to English keywords, we also applied search terms in the regional language (Tamil), such as *Maligai Kadai* (grocery shop), *Kalyana mandapam* (marriage hall).

The search results of each keyword were saved and merged in a single master file using ArcGIS V10.3. These search results contained many duplicates. We considered as 'pure duplicates' two or more cases where the name of the facility (e.g., "Kilpauk"), the type of facility (e.g. "Metro station"), and the coordinates (latitude and longitude) were all equal. These duplicates refer to a single facility that was found with multiple keywords in the same facility type (in the case of metro stations, the keywords were 'MRTS station', 'metro station', and 'suburban train station'). We considered as 'partial duplicates' one or more cases where the name of the facility, the latitude and the longitude were all equal, but the category labels were different. For instance, many facilities that appear in the search result of 'clothing' also appear in the search result for 'textiles'. Similarly, facilities listed under keywords 'beauty parlor', 'saloon' and 'spa' displayed a great deal of overlap and evidently referred to the same facilities that provide similar services. Duplicates, as based on the latitudes and longitudes of the facilities in the same facility type, were deleted.

A more complicated issue arises with respect to cross-category duplicates in the search results. In this case, identification by longitude and latitude is not enough, as multiple different and physically separated facilities can share coordinates because they are hosted in the same building. Therefore, to identify potential duplicates in the listed facilities we required them to not only share coordinates but also their names. Thus, two facilities with different coordinates, or with equal coordinates but different names, were assumed to not be duplicates.

If two (or more) facilities had the same coordinates and the same name but were listed with different functions, we assumed they hosted multiple functions and they were not seen as duplicates. For example, if two facilities with equal coordinates and names were

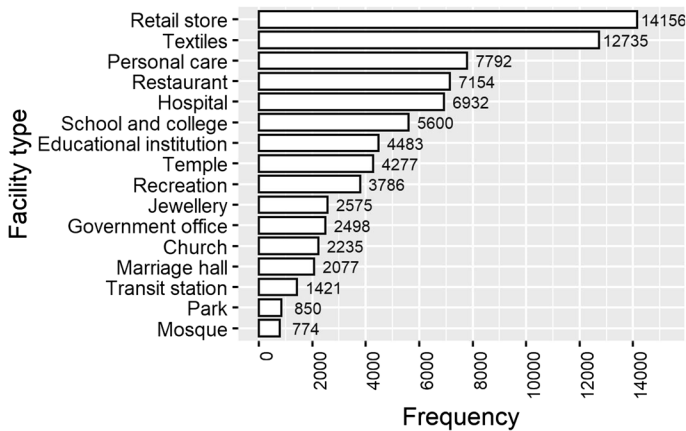


Fig. 2 Numbers of facilities in the study area (Chennai City)

listed under ‘textile store’ and ‘jewelry store’, we assumed the facility served both functions and none were deleted. An exception was made for those cases where one function evidently encompasses the other function. For example, as the more general category ‘educational institution’ includes schools and colleges, but also other educational institutions, the schools and colleges were excluded from the ‘educational institutions’ category, i.e., they were not separately counted as educational institutions.

To validate the Google Earth data, we physically verified the facilities in three randomly selected wards with field observations. The field investigation revealed that Google Earth correctly listed more than 95 percent of the facilities that were observed during the fieldwork. Point data of attributes generated from Google Earth Pro were converted as latitude and longitude using ArcGIS V10.3. In addition to the facilities, data on the size of each ward in terms of surface area and in terms of resident populations based on census 2011 counts, were obtained from the Greater Chennai Corporation database and included with other ward attributes. These features function as more general measures of opportunity, reflecting that even with equal numbers of facilities, larger and more populous wards may offer more criminal opportunities.

The frequencies of all the facilities in Chennai, aggregated over all 201 wards, are shown in Fig. 2. Textile stores and other retail stores are by far most frequent, followed by stores for personal care products and services, restaurants and ‘hospitals’ (which also include many small centers for outpatient medical and dental care).

Figure 3 presents a graphical overview of the Spearman correlation coefficients between the facility frequencies in wards. All correlations are positive, indicating that different types of facilities tend to agglomerate and lead to facility concentrations. Most correlations are medium-level, between 0.20 and 0.60. High correlations of ~0.85 exist between textile stores, personal care and other retail businesses.

Control Variables

Two variables, ward area and ward population, were included as control variables because they are likely to affect target availability generally without being directly linked to any

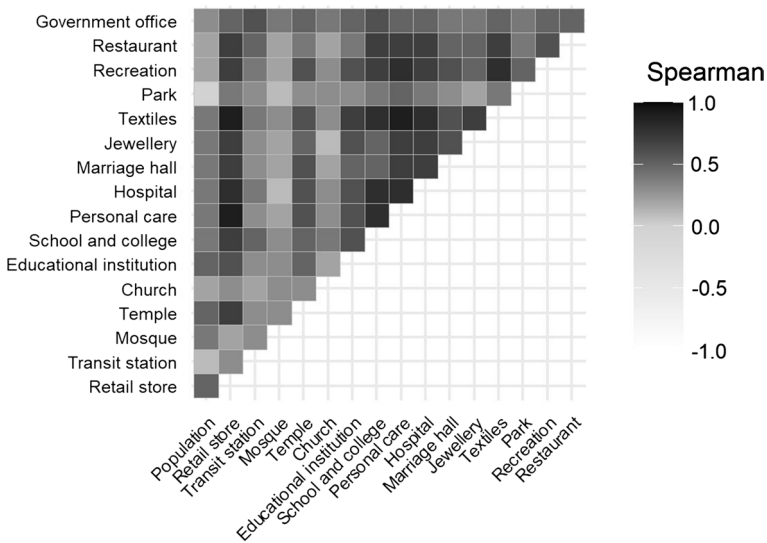


Fig. 3 Spearman correlation coefficients between facility frequencies in 201 wards

theoretical framework. First, as there is variability in the surface areas of the 201 wards, large wards are likely to provide more opportunities for snatching than small wards, even if both are equal in terms of distance, prior offences and numbers of crime generators and crime attractors, and population. Second, wards also vary in the size of the residential population. All else being equal, wards with larger populations may provide more snatching targets in public space than wards with smaller populations.

Methods

To quantify the spatial preferences of snatching offenders and test the hypotheses, we used the discrete crime location choice method (Bernasco and Nieuwebeerta 2005). This method applies McFadden’s random utility maximization theory (McFadden 2001) and econometric discrete choice models (Ben-Akiva and Lerman 1985; Train 2009) to the offender’s decision of where to commit crime. The method is well established in the field of offender spatial decision making (Ruiter 2017), and has been used in approximately 25 prior published studies (recent examples include Bernasco 2019; Frith et al. 2017; Menting 2018; Menting et al. 2020; Song et al. 2019; van Sleeuwen et al. 2018; Vandeviver and Bernasco 2020).

This discrete crime location choice method is particularly appropriate for two reasons. The first reason is the intimate link it provides between theory and statistical model. The method is rooted in random utility maximization theory, and uses statistical models (including amongst others the conditional, nested and mixed logit models) that are directly connected to this underlying theory. The direct link facilitates translating theoretical propositions into testable hypotheses about model estimates. The second reason is that the method uses a model of individual choice, in which it is possible to include idiosyncratic individual characteristics in the analysis. In case of crime location choice, it allows the analyst to include in the analysis locations that are part of each offender’s activity space. In particular the location of the offender’s residence has been

shown to have a consistently strong effect on where offenders commit crime (Ruiter 2017).

The discrete crime location choice method takes as a starting point an individual who is motivated to commit a snatching offense and is faced with the decision of where to commit it. It is assumed that the set of spatial alternatives the offender can choose from (the choice set) is discrete and countable. In this research, the offenders' choice set consists of the 201 wards in Chennai. According to utility maximization theory, the offender will compare all wards to establish which ward would maximize his expected offending utility when it would be the location of the offense.

To compare the 201 wards amongst each other, the offender assesses and compares their characteristics. Some of these characteristics are hypothesized to make the ward attractive for snatching (e.g., the presence of many affluent people in outdoor settings, the absence of guardianship) while others are hypothesized to render the ward unattractive (e.g., being located far away from the offender's residence). The actual choices of the offenders (where they committed snatching offenses) reveal to us the direction and relative importance of each of the decision criteria included in the model.

If the person committing snatching offense n decides to commit it in ward i , he or she must expect to derive more utility than any of the other 200 wards would provide:

$$U_{ni} > U_{nj} \forall j \neq i \quad (1)$$

According to random utility maximization theory, analysts have limited information. The sources of their uncertainty include unobserved attributes of the decision makers, unobserved attributes of the alternatives, and measurement error. To reflect this uncertainty, utility U_{ni} is modeled as a random variable that is the sum of a deterministic component V_{ni} representing the knowledge of the analysts, and a random error component ε_{ni} representing their uncertainty:

$$U_{ni} = V_{ni} + \varepsilon_{ni} \quad (2)$$

The probability that the person committing offense n chooses location i can thus be written as:

$$P_{ni} = Pr(U_{ni} > U_{nj} \forall j \neq i) = Pr(\varepsilon_{ni} - \varepsilon_{nj} < V_{ni} - V_{nj} \forall j \neq i) \quad (3)$$

If the unobserved random utility components ε_{ni} are independent and identically distributed according to an extreme value distribution, the *conditional logit model* (McFadden 1974) can be derived, in which

$$P_{ni} = \frac{e^{V_{ni}}}{\sum_{j=1}^J e^{V_{nj}}} \quad (4)$$

For computational convenience, and because any function can be closely approximated by a linear function, representative utility V_{ni} is assumed to be linear in the parameters:

$$V_{ni} = \beta' x_{ni} = \sum_{k=1}^K \beta_k x_{kni} \quad (5)$$

where K is the number of ward attributes x expected to be relevant for location decisions, x_{kni} is the value of attribute x_k of alternative i for decision-maker n , and β_k is a parameter associated with x_k that can be estimated when the actual choices have been observed. The log-likelihood of the conditional logit model is

$$l = \sum_{n=1}^N \left\{ \sum_{i=1}^J (y_{ni} \ln(P_{ni})) \right\} = \sum_{n=1}^N \left\{ \sum_{i=1, i \neq j}^J \left((y_{ni} \beta^i x_{ni}) - y_{ni} \ln \left(\sum_{j=1}^J e^{\beta^j x_{nj}} \right) \right) \right\} \quad (6)$$

where y_{in} is the observed choice, such that $y_{in} = 1$ if decision-maker n chooses alternative i and $y_{in} = 0$ if another alternative is chosen. From the size, direction and statistical significance of the estimated β parameters, conclusions can be drawn about the relevant criteria that offenders use when they decide where to commit a snatching offense.

By way of example, Model 1 in Table 3 is represented by the following equation:

$$V_{ni} = \beta_D D_{ni} + \beta_C C_{ni} + \beta_P P_i + \beta_A A_i \quad (7)$$

where D is distance, C is prior crimes, P is population, and A is area, where i indexes the 201 wards and n indexes the 1573 snatching offenses, and where the four β coefficients are estimates derived from the data.

The outcome of a conditional logit model is thus a set of estimated β coefficients, one for each explanatory variable. The estimated coefficients represent the direction and the strength of the relation between the explanatory variable and the offender's preference for a location. A corresponding set of standard errors quantifies the uncertainty about these estimated coefficients. The coefficients are most easily interpreted when transformed into odds ratios. Odds ratios range between 0–1 for negative effects (if they reduce the offender's preference for a location) and from 1 to infinity for positive effects (if they increase the offender's preference for a location). Odds ratios indicate by what factor the odds increase that the offender selects the location for committing an offence, if the value of the predictor variable raises by one unit. For example, if the estimated odds ratio of having committed prior offenses in the location is 2.0, then committing an offense in a previously unexploited location doubles the odds that the location will be selected for a future offense. Equivalently, not having offended at the location reduces of odds of targeting it by one half.

We first verified whether offenders' location preferences decreased with distance from their homes and increased with the number of prior snatching offenses in the location, and we explored the functional form of these relations. These analyses and their results are described in Appendix 2. Based on the outcomes, we used the *logarithm of distance* in subsequent analyses, and a dichotomy (none versus one or more) for the number of prior offenses in the location.

Before estimating the model we first calculated variance inflation factors (VIFs) and the condition number of the complete set of independent variables (Belsley 1991a, 1991b; O'Brien 2007). No degenerating collinearity issues were present. Detailed results of this supporting analysis are reported in Appendix 3.

Results

Table 3 presents the results of two conditional logit models. The first column holds the names of the predictor variables. It includes in parenthesis the units in which they were entered into the model. Thus, effects of distance are per kilometer, effects of population per thousand residents and effects of churches are given per 10 churches. The other columns present, for each of the two models, the estimated odds ratios and the lower and upper bounds of their 95% confidence intervals. If the upper and lower bounds of the confidence

Table 3 Conditional logit model estimates. Number of snatchings is 1573, number of wards is 201, and total number of observations is $1573 \times 201 = 316,173$

	Model 1		Odds Ratio	Model 2		
	Odds ratio	95% Confidence interval		95% Confidence interval		
		Lower			Upper	Lower
Distance (km)	0.36*	0.35	0.38	0.35*	0.34	0.37
Any prior crimes (0,1)	12.72*	9.59	16.86	10.72*	8.08	14.23
Area (km ²)	1.15*	1.12	1.18	1.07*	1.03	1.11
Population (# 1000)	1.03*	1.02	1.03	1.00	1.00	1.01
Retail stores (# 10)				1.01	0.99	1.03
Transit stations (# 10)				1.03	0.94	1.13
Mosques (# 10)				1.07	0.89	1.29
Temples (# 10)				1.01	0.95	1.07
Churches (# 10)				1.18*	1.09	1.28
Education institutions (# 10)				1.07*	1.04	1.11
School and college (# 10)				0.99	0.94	1.04
Personal care (# 10)				1.07*	1.02	1.11
Hospitals (# 10)				1.00	0.97	1.03
Marriage halls (# 10)				1.13*	1.04	1.22
Jewelleries (# 10)				1.02	0.99	1.06
Textiles (# 10)				0.99	0.97	1.00
Park (# 10)				1.17*	1.02	1.34
Recreation facilities (# 10)				0.95	0.90	1.01
Restaurant (# 10)				1.03*	1.00	1.06
Government office (# 10)				1.06*	1.01	1.11
AIC	14,749.27			14,504.19		

* $p < .05$

interval are either both below 1 or both above 1, the odds ratio is statistically significant at $p < 0.05$ (two-sided).

Distance Hypothesis

The estimated odds ratio of the log-distance effect is 0.36 in Model 1 and 0.35 in Model 2. It indicates that if a ward is further away from the offender's home, the odds of the offender selecting the ward for snatching decrease. The estimated effect is linear in the logarithm of distance, but loglinear in distance itself. The value of 0.35 represents the change in the offender's odds of selecting a ward that is caused by a one-unit change in the logarithm of

distance. This implies that a given difference at the lower side of the distance scale has a larger effect than the same difference at the right side of the scale. By way of example, the value of 0.35 means that the odds of selecting a ward decrease by a factor 0.78 (by 22 percent) as the distance to that ward doubles, e.g. from 250 to 500 m, from 500 m to 1,000 m, from 1,000 to 2,000 m, and so on.¹ Thus, the decrease is steep at smaller distances and subsequently flattens out with increasing distance.² The confidence interval is very small, between 0.34 to 0.37, which indicates that the findings are statistically significant and confirm the *distance hypothesis*.

Repeat Offending Hypothesis

The next hypothesis is the *repeat offending hypothesis*. Both Model 1 and Model 2 confirm that wards in which the offender has previously offended are much more likely to become targets of the same offender than wards where the offender never offended. The odds ratios of 12.72 in Model 1 and 10.72 in Model 2 are quite similar, and indicate a large and statistically significant effect: the odds of selecting a ward are ~12 times larger if the offender has previously committed a snatching offense in the ward than if the offender had not committed a previous snatching offense in the ward. This is strong evidence to support the repeat offending hypothesis.

Crime Generators and Attractors Hypothesis

In the *crime generators and attractors hypothesis*, we assumed that larger numbers of facilities in a ward increase the availability of suitable snatching targets to offenders, in particular if the potential victims carry CRAVED items. As a result, offenders were expected to prefer wards with larger number of facilities. The hypothesis translates into several partial hypotheses, one for each type of facility distinguished.

Based on Table 3, the evidence for this hypothesis is mixed. Whereas we find that the estimated effects of some types of facilities are positive and statistically significant (churches, educational institutions, marriage halls, personal care businesses, parks, restaurants and business offices), the majority are not. Of the six facilities for which we do find significant positive effects, those of churches (1.18), marriage halls (1.13) and parks (1.17) appear relatively large. For example, if a ward has 10 more churches than a similar other ward, the odds of the offender preferring the first ward are 16 percent larger than the offender preferring the second ward. This is presumably in part a consequence of the average numbers of visitors that facilities attract (e.g., one park likely attracts more visitors than one restaurant).

Discussion and Conclusion

The present research investigated the location choices of snatching offenders in Chennai, India. As the large majority of prior studies on crime location choices have been conducted in western countries, it is important not only to verify whether the established relationships

¹ The calculation is $e^{.35(\log(.5))} = .78$, with distance expressed in kilometers.

² In otherwise equivalent models with untransformed distance (which fit the data slightly less well) the odds ratio estimate of distance is .81, which means that the odds of selecting the ward decrease by 19 percent for every kilometer the ward is farther away from the offender's home.

also hold in other regions of the world, but also to make sure that key theoretical concepts are measured in a way that reflects relevant local economic, social and cultural characteristics. Our analysis of snatching location choices in India, for example, emphasized the potential relevance of specific places (marriage halls and places of worship) where many people wear valuable jewelry and clothing ornaments in outdoor settings.

Our study aimed to replicate three findings in the extant literature: (1) the preference of offenders for locations near their residence, (2) the preference of offenders for locations where they offended before, and (3) the preference of offenders for locations where suitable targets are abundant. Our study replicated findings (1) and (2), and found mixed results for (3).

As the extant literature has consistently confirmed that offenders prefer to offend in the proximity of their homes and not in distant locations (Ruiter, 2017), it may not come as a surprise that we found the same tendency in snatching offenders in Chennai. To compare the effect size with those of other studies, we here use the estimated odds ratio for a model with untransformed distance. The odds ratio is 0.81 (see footnote 2), a value that is in line with effect sizes found in other studies on various offense types, e.g. Menting (2018) (OR=0.69), Menting et al. (2016) (OR=0.72), Bernasco (2010b) (OR=0.74), (OR=0.82), and Bernasco and Kooistra (2010) (OR=0.91).

We found that offenders who reoffended in the study period were more likely to return to wards where they offended before than to other wards. This effect size (OR=13) is larger than what has been found in prior studies that investigated the hypothesis, e.g. (Menting et al. 2016) (OR=5.9)(Lammers et al. 2015) (OR=7.2). This might be due to variations between samples and between crime types in the average time between repeat offenses, because it has been demonstrated that the tendency of offenders to return to prior offense locations becomes weaker as the time between the offenses increases (Bernasco et al. 2015; Long et al. 2018).

The evidence supporting the distance hypothesis and the repeat offending hypothesis is in line with the predictions of crime pattern theory, which emphasizes the constraining role that personal awareness space and personal experiences play in determining location choices of offenders: offenders are most likely to offend in places they are familiar with.

Crime pattern theory also states that certain facilities—crime generators and crime attractors—pull offenders because these facilities bring together many people and thus increase the availability of suitable targets. With respect to the effects of these crime generators and crime attractors, we find mixed results. The presence of many types of facilities does not appear to affect offenders' preferences for wards. For example, temples were expected to attract snatching offenders because many people visit temples and many of them wear valuable jewels and other accessories during their visits. We did find six types of facilities to be significantly and positively related to offenders' preferences. Two of them, churches and marriage halls, are clearly places where many people go wearing valuable jewels and accessories. For the four others, the link with CRAVED items is less clear: parks, educational institutions, business offices and personal care businesses.

Limitations

Our study has some limitations that restrict its generality and should be emphasized. Most of these limitations apply to the level of detail and representativeness of the data. First, the spatial units of analysis in this study, the 201 wards of Chennai City, have an average surface area of 2.18 km² and an average population of 33,195. Contemporary work on *crime*

at places (Lee et al. 2017; Weisburd et al. 2009) emphasizes the heterogeneity of such large units and suggests that crime better be studied at more fine-grained resolutions, such as streets, street segments or parcels, as this could better reflect the very local nature of crime attractors and generators and guardianship. In fact, some crime location studies have started to utilize small spatial units of analysis (e.g., Bernasco 2010a; Frith et al. 2017; Vandeviver et al. 2015). Although population is only measured at ward level and although the spatial precision of the geocoding of snatching offenses is not perfect, our data actually consists of objects (offender residence, crime locations and facilities) that are geo-coded as coordinates and could thus be aggregated to sizes and shapes other than ward boundaries and potentially be linked to data from the OpenStreetMap project (see www.openstreetmap.org). However, a multiple-scale analysis would require additional research questions, a new design and analytical strategy, and would go far beyond the purposes and ambitions of the present study.

Second, the data on snatching offenses reflect only a very small fraction of the snatching offenses suffered by victims. Not only is just about one third of the snatching offenses reported to the police detected, it is estimated that only 6–8 percent of theft victims (including victims of snatching) report to the police (Durani et al. 2017). Although all victim underreporting jeopardizes generalizations, the very high underreporting of snatching offenses in Chennai creates an elevated potential of selectivity in our sample. The international literature on reporting to the police demonstrates that whether victims report to the police depends not only on the seriousness of the offense but also on attributes of the victims themselves and of the offenders. It is plausible that this also applies in India. For example, in a study that measured the subjective level of control of victims who did report to the police, Vinod Kumar (2015) found that least control was experienced by members of groups holding the most disadvantaged positions in Indian society, i.e. women, the less wealthy, the lower educated and members of groups in the lower ranks of the caste-based hierarchy that has been a system of social stratification in Indian society. It seems plausible that if these groups experienced less control in their contacts with the police, they might also be less inclined to report victimization in the first place. This might imply that our findings are more representative of snatching incidents in which male, wealthy and educated individuals were victimized, than of a random sample of snatching incidents. These considerations force us to formulate our conclusions tentatively.

A third limitation applies the data on facilities that we accessed in Google Earth. Although the coverage of facilities appears sufficient (fieldwork observations suggested a coverage of more than 95 percent of the facilities), the data do not allow facilities to be differentiated by size. Even facilities of the same type (e.g. hospital, church, or store) can vary widely in the number of visitors they attract, but this variation is not reflected in our facility frequencies.

A final limitation, one that applies to all published crime location choice studies using the discrete spatial choice framework, is that our findings cannot identify the intentions that motivate offenders' mobility. The crime location choice model cannot distinguish between the choice of *whether* to commit crime (given the location where the individual is) and the choice of *where* to commit crime (given sufficient motivation to commit it). This is an important distinction that hinges on the offender's level of premeditation, i.e. on the extent to which the offense is planned in advance. We

do not have direct evidence on the level of premeditation of the snatching offenses in our data.³ Some offenders may have visited the crime location with the specific aim of snatching. Others may have been present at the location for purposes completely unrelated to crime (e.g., work, school, travel, entertainment, exercise, or shopping) and have encountered a snatching opportunity they could not resist. In the latter case, the offenders did not choose the location with criminal intentions. Despite this ambiguity in the interpretation of choice outcomes at the individual level, the estimated coefficients of the discrete choice model are valid indicators of how land use categories affect the criminal attractiveness of potential target areas. In fact, the conditional logit model without inclusion of the home-crime distance variable is completely equivalent to a Poisson model of snatching frequencies across the 201 Chennai wards (Guimaraes et al. 2003; Schmidheiny and Brülhart 2011), which is a common model to analyze the spatially aggregated variability of crime.

Future Research

The results of our study suggest some possible directions for future research. The first applies to temporal variations. Many studies have demonstrated that crime frequencies vary by time of day, by day of week and by season (Andresen and Malleson 2013; Haberman and Ratcliffe 2015; Tompson and Bowers 2013) and some studies have examined whether location preferences also vary temporally (van Sleeuwen et al. 2018). With respect to snatching offenses, a plausible hypothesis could be that the availability of targets will vary both over space and time, and thus be related not only to where crime generators and attractors are located, but also on when they are visited.

Although location choice studies have been conducted with spatial units of varying levels of granularity, ranging from neighborhoods down to individual addresses, what seems to be lacking in the literature is a systematic analysis of the extent to which the findings of location choice studies depend on the shapes, sizes and nesting structures of the spatial units of analysis. Are the estimated coefficients of the models scale-free, do they depend on spatial scale, or should they even be studied in a nested structure (where, for example, the effect of a facility on an offender's preference for a street block depends on higher-level neighborhood attributes)?

Location preferences of offenders are influenced by their awareness space (Brantingham et al. 2017). Replicating prior findings (Bernasco et al. 2015; Lammers et al. 2015; Long et al. 2018), the present study investigated the effects of offenders' home locations and of their prior offending locations. Future research could focus on effects of offenders' work place, previous residences and other anchor points that are part of their awareness space and have a possible impact on their offending location choices.

A few studies have confirmed the possible effect of co-offending on location choice (Cromwell et al. 1991; Garcia-Retamero and Dhami 2009; Hearnden and Magill 2004; Xiao et al. 2018). Hence, future research on snatching could study possible effects of co-offending. Further, situational measures of guardianship such as police presence,

³ Occasionally police data may contain information on preparatory actions, such as whether offenders carry tools with them that signal criminal intentions (e.g. gun, knife, crowbar, disguise clothing).

CCTV cameras, whether the victim is alone or accompanied and presence of people who can act as natural guardians are promising options for future research.

Finally, although our findings suggest that theories and methods developed in western cultures can be applied with limited modifications in the Indian urban context of Chennai City, the evidence base would be strengthened by replications of the findings, elsewhere in India and elsewhere in the world. An obvious question to be addressed is how the concept of crime generators and crime attractors can be reliably operationalized in non-western cultures. Other pending questions relate to the mobility patterns of offenders and how they affect their awareness space.

Appendix 1: Google Earth Search Keywords per Facility Category

Keyword	Facility category	Joined categories
MRTS station	Train station	Transit station
Metro station		
Suburban train station		
Bus stop	Bus stop	
Bus depot		
Vegetable market	Vegetable market	Retail store
Supermarket	Supermarket	
General store	General store	
Maligai kadai		
Medical shop	Medical shops	
Park	Park	Park
Recreation	Recreation	Recreation
Marriage hall	Marriage hall	Marriage hall
Kalyana Mandapam		
Temple	Temple	Temple
Church	Church	Church
Mosque	Mosque	Mosque
School and college	Schools and colleges	Schools and colleges
Educational institution	Educational institution	Educational institution
Hospital	Hospital	Hospitals
Clinic		
Government office	Government office	Government office
Saloon	Saloon	Personal care
Beauty parlor	Beauty parlor	
Barber shop	Barber shop	
Spa	Spa	
Jewelry shop	Jewelry shop	Jewelry shop
Restaurant	Restaurants	Restaurants
Dining		
Clothing	Textile stores	Textile stores
Textiles		
Fashion		

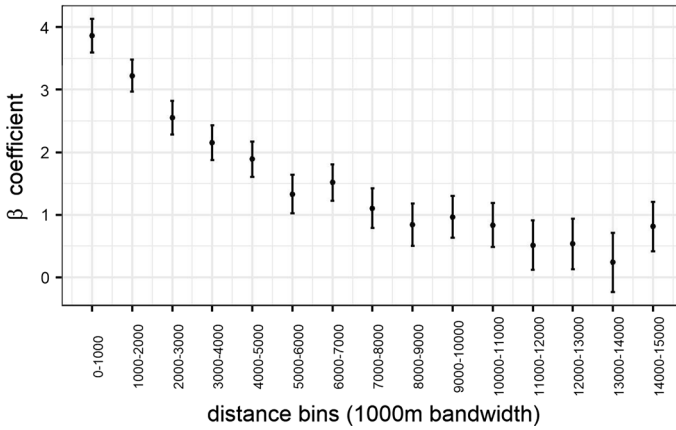


Fig. 4 Conditional Logit Estimates of distance in 1000 m bins. Reference category is 15000+m

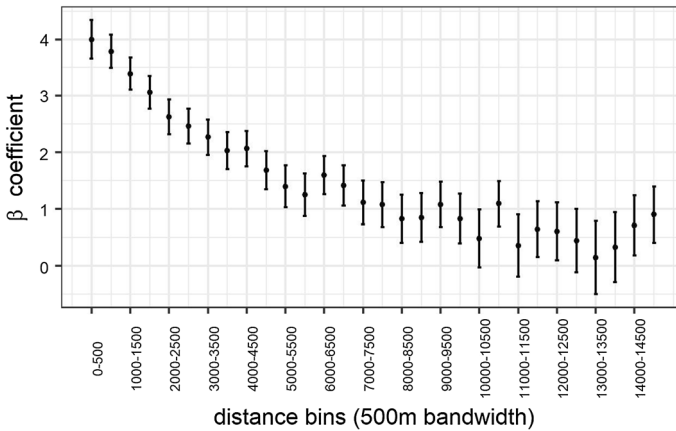


Fig. 5 Conditional Logit Estimates of distance in 500 m bins. Reference category is 15000+m

Appendix 2: Location Preference Relations with Distance and Number of Prior Crimes

To explore the functional form of the relation between location preference and distance to home, we recoded distance into discrete bins, and estimated the conditional logit model with a dichotomous dummy variable for each bin.

We applied three alternative schemes to recode distance into discrete bins, using bandwidths of 1000, 500 and 250 m respectively. For all three schemes, distances beyond 15 km (the 95th percentile in the sample) were included as the reference category. The advantage of a small bandwidth is high spatial granularity, the disadvantage is that the standard error is relatively large because there are fewer observations per bin. Larger bandwidths have smaller standard errors but provide less spatial granularity. Figures 4, 5 and 6 visualize the β point estimates (dots) and their 95% confidence intervals (vertical lines) of these three conditional logit models. All three consistently

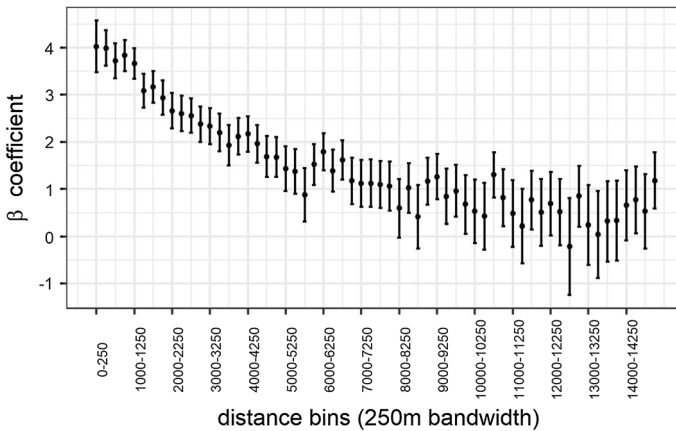


Fig. 6 Conditional Logit Estimates of distance in 250 m bins. Reference category is 15000+ m

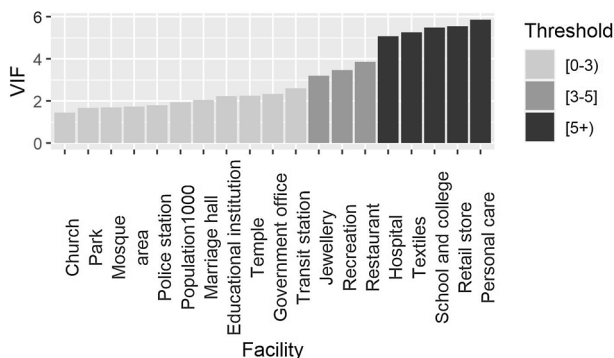
show a curve that slopes down in an almost perfectly monotonical way. Visual inspection suggests that during the first 6 km the decay is almost linear. Beyond that point it becomes convex, suggesting exponential decay. To address this convexity (and because exponential decay in distance implies linear decay in the logarithm of distance), many prior crime location studies have used a logarithmic distance transformation (Bernasco 2010a; Bernasco and Block 2009; Bernasco et al. 2013, 2017; Long et al. 2018).

To assess model fit, we estimated two models, one with untransformed distance as a covariate and one with the logarithm of distance as a covariate, and compared the values of the Bayesian Information Criterion (BIC) and the Akaike Information Criterion (AIC). Because it had lower values on both the BIC and the AIC, the model with the logarithmic distance specification was superior. It had also superior fit when other covariates were added to the model (in Model 1 and Model 2 in Table 3).

We further checked whether location preferences monotonically increased in the number of prior snatching offenses in the location. The number of prior snatching offenses was categorized as either 1 or 2–3 prior snatching offenses (with 0 prior snatching offenses serving as the reference category).⁴ The results of this exploratory model show that the differential effects of 1 prior offense versus 2–3 prior offenses is negligible: the odds ratios are 13.13 and 15.19 respectively, with substantial overlap between the 95% confidence intervals. Based on these results, in the subsequent analyses we merged both categories, and thus used a dichotomous variable to indicate whether the offender had committed any prior snatching offenses in the focal area.

⁴ In the data there were 754 instances of 1 prior offense in the location, 66 instances of 2 prior offenses in the location and 3 instances of 3 prior offenses in the location. Therefore, the last two categories were joined.

Appendix 3: Variance Inflation Factors



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References

- Andresen MA, Malleon N (2013) Crime seasonality and its variations across space. *Appl Geogr* 43:25–35. <https://doi.org/10.1016/j.apgeog.2013.06.007>
- Ansari S, Verma A, Dadkhah KM (2015) Crime Rates in India: A Trend Analysis. *Int Crim Justice Rev* 25(4):318–336. <https://doi.org/10.1177/1057567715596047>
- Belsley DA (1991a) Conditioning Diagnostics. Collinearity and Weak Data in Regression. Wiley, New York
- Belsley DA (1991b) A Guide to using the collinearity diagnostics. *Comp Sci Econom Manag* 4(1):33–50. <https://doi.org/10.1007/BF00426854>
- Ben-Akiva ME, Lerman SR (1985) *Discrete Choice Analysis: Theory and Application to Travel Demand*. MIT Press, Cambridge, MA
- Bernasco W (2008) Them again? same offender involvement in repeat and near repeat burglaries. *Eur J Criminol* 5(4):411–431. <https://doi.org/10.1177/1477370808095124>
- Bernasco W (2010a) Modeling micro-level crime location choice: application of the discrete choice framework to crime at places. *J Quant Criminol* 26(1):113–138. <https://doi.org/10.1007/s10940-009-9086-6>
- Bernasco W (2010b) A sentimental journey to crime: effects of residential history on crime location choice. *Criminology* 48:389–416. <https://doi.org/10.1111/j.1745-9125.2010.00190.x>
- Bernasco W (2019) Adolescent offenders' current whereabouts predict locations of their future crimes. *PLoS ONE* 14(1):e0210733. <https://doi.org/10.1371/journal.pone.0210733>
- Bernasco W, Block R (2009) Where offenders choose to attack: a discrete choice model of robberies in Chicago. *Criminology* 47(1):93–130. <https://doi.org/10.1111/j.1745-9125.2009.00140.x>

- Bernasco W, Block R (2011) Robberies in Chicago: a block-level analysis of the influence of crime generators, crime attractors and offender anchor points. *J Res Crime Delinq* 48(1):33–57. <https://doi.org/10.1177/0022427810384135>
- Bernasco W, Kooistra T (2010) Effects of residential history on commercial robbers' crime location choices. *Eur J Criminol* 7(4):251–265. <https://doi.org/10.1177/1477370810363372>
- Bernasco W, Nieuwbeerta P (2005) How do residential burglars select target areas? A new approach to the analysis of criminal location choice. *Br J Criminol* 45:296–315. <https://doi.org/10.1093/bjc/azh070>
- Bernasco W, Block R, Ruiter S (2013) Go where the money is: modeling street robbers' Location choices. *J Econom Geograp* 13(1):119–143. <https://doi.org/10.1093/jeg/lbs005>
- Bernasco W, Johnson SD, Ruiter S (2015) Learning where to offend: effects of past on future burglary locations. *Appl Geogr* 60:120–129. <https://doi.org/10.1016/j.apgeog.2015.03.014>
- Bernasco W, Ruiter S, Block R (2017) Do street robbery location choices vary over time of day or day of week? A test in Chicago. *J Res Crime Delinq* 54(2):244–275. <https://doi.org/10.1177/0022427816680681>
- Brantingham PJ, Brantingham PL (1995) Criminality of place: crime generators and crime attractors. *Eur J Crimin Policy Res* 3(3):5–26. <https://doi.org/10.1007/BF02242925>
- Brantingham PJ, Brantingham PL, Andresen MA (2017) The geometry of crime and crime pattern theory. In: Criminology E, Analysis C (eds) R Wortley, M Townsley. Routledge, Abingdon, pp 98–116
- Chen J, Liu L, Zhou S, Xiao L, Song G, Ren F (2017) Modeling spatial effect in residential burglary: a case study from ZG City. *China ISPRS Int J Geo-Inf* 6(138):1–13. <https://doi.org/10.3390/ijgi6050138>
- Clarke RV (1999) *Hot Products: Understanding, Anticipating and Reducing Demand for Stolen Goods*. Home Office, London
- Clarke P, Ailshire J, Melendez R, Bader M, Morenoff J (2010) Using google earth to conduct a neighborhood audit: reliability of a virtual audit instrument. *Health Place* 16(6):1224–1229
- Cromwell PF, Olson JN, Marks A (1991) How drugs affect decisions by burglars. *Int J Offender Therap Comparat Criminol* 35(4):310–321
- Curran, K, Dale, M, Edmunds, M, Hough, M, Millie, A, Wagstaff, M. (2005). *Street crime in London: deterrence, disruption and displacement*. Retrieved from London
- Durani A, Kumar R, Sane R, Sinha N (2017) Safety trends and reporting of crime. IDFC Institute, Mumbai
- Everson S, Pease K (2001) Crime against the same person and place: Detection opportunity and offender targeting. In: Farrell G, Pease K (eds) Repeat victimization. Criminal Justice Press, Monsey, pp 199–220
- Frith MJ, Johnson SD, Fry HM (2017) Role of the street network in burglars' spatial decision making. *Criminology* 55(2):344–376. <https://doi.org/10.1111/1745-9125.12133>
- Garcia-Retamero R, Dhami MK (2009) Take-the-best in expert-novice decision strategies for residential burglary. *Psychon Bull Rev* 16(1):163–169
- Glasner P, Johnson SD, Leitner M (2018) A comparative analysis to forecast apartment burglaries in Vienna, Austria, based on repeat and near repeat victimization. *Crime Sci* 7(9):1–13
- Goudriaan H, Wittebrood K, Nieuwbeerta P (2006) Neighbourhood characteristics and reporting crime. *Br J Criminol* 46(4):719–742. <https://doi.org/10.1093/bjc/azi096>
- Guimaraes P, Figueirido O, Woodward D (2003) A tractable approach to the firm location decision problem. *Rev Econ Stat* 85(1):201–204
- 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
- Hearnden, I, Magill, C. (2004). *Decision-making by house burglars: offenders' perspectives* (Home Office Research Findings 249). Retrieved from London
- Hockey D (2016) Burglary crime scene rationality of a select group of non-apprehend burglars. *SAGE Open* 6(2):1–13. <https://doi.org/10.1177/2158244016640589>
- Jaishankar K, Shanmugapriya S, Balamurugan V (2009) Crime mapping in india : a GIS implementation in Chennai City policing. *Geograph Inf Sci* 10(1):20–34. <https://doi.org/10.1080/10824000409480651>
- Johnson SD, Bernasco W, Bowers KJ, Elffers H, Ratcliffe J, Rengert G, Townsley MT (2007) 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, 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>
- Kelly CM, Wilson JS, Baker EA, Miller DK, Schootman M (2012) Using google street view to audit the built environment: inter-rater reliability results. *Annal Behavior Med* 45(1):S108–S112. <https://doi.org/10.1007/s12160-012-9419-9>

- 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>
- Lee Y, Eck JE, O, S, Martinez, NN. (2017) How concentrated is crime at places? A systematic review from 1970 to 2015. *Crime Sci* 6(1):6. <https://doi.org/10.1186/s40163-017-0069-x>
- Long D, Liu L, Feng J, Zhou S, Jing F (2018) Assessing the influence of prior on subsequent street robbery location choices: a case study in ZG City. *China Sustain* 10(6):1818. <https://doi.org/10.3390/su10061818>
- McFadden D (2001) Economic choices. *Am Econom Rev* 91(3):351–378. <https://doi.org/10.1257/aer.91.3.351>
- Menting B (2018) Awareness \times opportunity: testing interactions between activity nodes and criminal opportunity in predicting crime location choice. *Br J Criminol* 58(5):1171–1192. <https://doi.org/10.1093/bjcr/azx049>
- Menting B, Lammers M, Ruiter S, Bernasco W (2016) Family matters: effects of family members' residential areas on crime location choice. *Criminology* 54(3):413–433. <https://doi.org/10.1111/1745-9125.12109>
- Menting B, Lammers M, Ruiter S, Bernasco W (2020) The influence of activity space and visiting frequency on crime location choice: findings from an online self-report survey. *Br J Criminol* 60(2):303–322. <https://doi.org/10.1093/bjcr/azx044>
- Monk KM, Heinonen JA, Eck JE (2010) Street robbery. Department of Justice, Office of Community Oriented Policing Services, Washington, D.C
- Nee C, van Gelder J-L, Otte M, Vernham Z, Meenaghan A (2019) Learning on the job: studying expertise in residential burglars using virtual environments. *Criminology* 57(3):481–511. <https://doi.org/10.1111/1745-9125.12210>
- O'Brien RM (2007) A caution regarding rules of thumb for variance inflation factors. *Qual Quant* 41(5):673–690. <https://doi.org/10.1007/s11135-006-9018-6>
- OLA Mobility Institute. (2018). *Ease of Moving Index*. Retrieved from New Delhi, India: <https://ola.institute/ease-of-moving/>
- Patel M (2016) Crime by youth: easy money spurs to chain snatchers. *Int J Criminol Sociol Theor* 9(1):1–13
- Prasad K (2013) A comparison of victim-reported and police-recorded crime in India. *Econ Pol Wkly* 48(33):47–53
- Ratcliffe JH, Rengert GF (2008) Near-repeat patterns in philadelphia shootings. *Secur J* 21(1):58–76. <https://doi.org/10.1057/palgrave.sj.8350068>
- Rengert GF, Wasilchick J (1985) Suburban Burglary: A Time and Place for Everything. Charles C. Thomas, Springfield, IL
- Ruiter S (2017) Crime Location Choice: State of the Art and Avenues for Future Research. In: Bernasco W, Van Gelder J-L, Elffers H (eds) *The Oxford Handbook of Offender Decision Making*. Oxford University Press, Oxford, UK, pp 398–420
- Schmidheiny K, Brühlhart M (2011) On the equivalence of location choice models: conditional logit, nested logit and Poisson. *J Urban Econ* 69(2):214–222. <https://doi.org/10.1016/j.jue.2010.09.004>
- Sivamurthy A (1989) Pattern of house - burglary: the application of centro graphic technique. *Indian J Criminol* 17(1):53–57
- Sivasankar S, Sivamurthy A (2016) Application of centro graphic technique, pattern of property crimes in chennai city: a gis based approach. *Indian Police J* 63(2):152–159
- Song G, Bernasco W, Liu L, Xiao L, Zhou S, Liao W (2019) Crime feeds on legal activities: daily mobility flows help explain thieves' target location choices. *J Quant Criminol* 35:831–854. <https://doi.org/10.1007/s10940-019-09406-z>
- Taylor JR, Lovell ST (2012) Mapping public and private spaces of urban agriculture in Chicago through the analysis of high-resolution aerial images in Google Earth. *Landsc Urban Plan* 108(1):57–70. <https://doi.org/10.1016/j.landurbplan.2012.08.001>
- Tompson L, Bowers K (2013) A stab in the dark?: a research note on temporal patterns of street robbery. *J Res Crime Delinq* 50(4):616–631. <https://doi.org/10.1177/0022427812469114>
- Townsley MT, Birks D, Bernasco W, Ruiter S, Johnson SD, White G, Baum S (2015) Burglar target selection: a cross-national comparison. *J Res Crime Delinq* 52(1):3–31. <https://doi.org/10.1177/0022427814541447>
- Townsley MT, Birks D, Ruiter S, Bernasco W, White G (2016) Target selection models with preference variation between offenders. *J Quant Criminol* 32(2):283–304. <https://doi.org/10.1007/s10940-015-9264-7>
- Train, KE. (2009). *Discrete Choice Methods with Simulation* (2nd ed ed.). New York.
- 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>

- Vandeviver C, Bernasco W (2020) “Location, location, location”: effects of neighborhood and house attributes on burglars’ target selection. *J Quant Criminol* 36(4):779–821. <https://doi.org/10.1007/s10940-019-09431-y>
- Vandeviver C, Neutens T, van Daele S, Geurts D, Vander Beken T (2015) A discrete spatial choice model of burglary target selection at the house-level. *Appl Geogr* 64:24–34. <https://doi.org/10.1016/j.apgeog.2015.08.004>
- Vinod Kumar TK (2015) Impact of demographic characteristics of crime victim on interaction with police in india—gender, caste, class and police response. *South Asian Survey* 22(1):54–77. <https://doi.org/10.1177/0971523117714091>
- Weisburd D, Bernasco W, Bruinsma GJN (eds) (2009) *Putting Crime in its Place: Units of Analysis in Geographic Criminology*. Springer, New York
- Wiles P, Costello A (2000) *The “road to nowhere”: the evidence for traveling criminals*. Home Office, Research, Development and Statistics Directorate, London
- World Gold Council. (n.d.). Geographical diversity of gold demand. Retrieved from <https://www.gold.org/about-gold/gold-demand/geographical-diversity/india>
- Xiao L, Liu L, Song G, Ruiters S, Zhou S (2018) Journey-to-crime distances of residential burglars in china disentangled: origin and destination effects. *ISPRS Int J Geo Inf* 7(8):325. <https://doi.org/10.3390/ijgi7080325>

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