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Crime Feeds on Legal Activities: Daily Mobility Flows Help to Explain Thieves' Target Location Choices

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Abstract

Objective According to routine activity theory and crime pattern theory, crime feeds on the legal routine activities of offenders and unguarded victims. Based on this assumption, the present study investigates whether daily mobility flows of the urban population help predict where individual thieves commit crimes.

Methods Geocoded tracks of mobile phones are used to estimate the intensity of population mobility between pairs of 1616 communities in a large city in China. Using data on 3436 police-recorded thefts from the person, we apply discrete choice models to assess whether mobility flows help explain where offenders go to perpetrate crime.

Results Accounting for the presence of crime generators and distance to the offender's home location, we find that the stronger a community is connected by population flows to where the offender lives, the larger its probability of being targeted.

Conclusions The mobility flow measure is a useful addition to the estimated effects of distance and crime generators. It predicts the locations of thefts much better than the presence of crime generators does. However, it does not replace the role of distance, suggesting that offenders are more spatially restricted than others, or that even within their activity spaces they prefer to offend near their homes.

Keywords Crime location choice · Theft from the person · Mobility · Routine activities · China

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Introduction

Opportunity theories of crime assume that most crimes take place while the victims and the offenders are involved in non-criminal routine activities. Even crimes that are premeditated and that are not perpetrated during the offenders' routine activities, are nevertheless supposed to be informed by what offenders heard, saw, read or picked up otherwise during non-criminal daily routines. In their introduction of routine activity theory, Cohen and Felson (1979) summarize this position by stating that "illegal activities feed upon the legal activities of everyday life" (p. 588). In outlining crime pattern theory, Brantingham and Brantingham (2008) take the same position by stating that "what shapes non-criminal activities helps shape criminal activities" (p. 79). The present study aims to test this key assumption of opportunity theories. To do so, it puts front stage the daily mobility flows of the urban population as measured by the tracks of mobile phones and assesses whether these mobility flows help predict where individual thieves commit crimes. The key question is thus one that precisely describes the criminal location choice approach (Bernasco and Nieuwbeerta 2005): Given the home location of an offender motivated to commit a crime and given the locations of all potential targets, can we understand and predict where the offender commits the offense? Whereas prior crime location studies have included only the home-target distance (and occasionally also measures of physical and social barriers) to explain crime location choice (Ruiter 2017), the present study explores whether the explanation can be improved by considering the movement patterns of the general population as a 'spatial template' for the journey to crime.

Background

In trying to understand and predict where individual offenders go to commit crimes, it is important to consider their journey to crime, which links their home location to where they commit crime (Rengert 2004). Two empirical observations seem undisputed. The first observation is that the frequency of crime displays *distance decay*: it decreases with the distance from the offender's home (Rossmo 2000). The median distance between the offender's home and the crime location is no more than a mile, with some variation observed across crime types and offender categories (Townsley and Sidebottom 2010). Research in human geography has demonstrated that distance decay also characterizes non-criminal routine activities like working, visiting friends or shopping. The distribution of daily human travel distances, including presumably those of offenders, follows a power law function: Most of our trips are over short distances whereas occasionally we take longer trips (Gonzalez et al. 2008). Thus, legal and illegal trips both display a distance decay pattern. Although distance from home is not an explicit element of opportunity theories, its empirical relevance is evident.

The second undisputed observation about crime locations is that crime is geographically concentrated at and around *crime generators*, micro-places where many people converge on a regular basis to pursue similar or complementary activities (Brantingham and Brantingham 1995). Crime generators include transit stations, shopping centers, schools, sports venues, entertainment areas and other types of facilities. Crime generators produce crime for two reasons. First, because they are popular destinations for many legal activities, they are known to a large proportion of the population, including potential offenders. They are an element of their activity space. Second, these micro-places

often provide specific opportunities for crime, especially when they are being visited by large crowds of people. For example, shops provide opportunities for shoplifters, distracted passengers at subway stations are easy targets for pickpockets, and intoxicated patrons leaving bars are vulnerable for robbery (Bernasco and Block 2011). In sum, crime generators produce crime because they are widely known and because they provide abundant opportunities. Empirical evidence thus demonstrates that offenders generally commit crimes around busy places located within at most a few miles from their homes, depending on the crime type, the size of the city and the convenience of available transportation.

These two observations on distance decay and crime generators, however, do not determine with much precision where individual offenders perpetrate their crimes. The area within one mile of an offender's home already covers 3.14 square miles. The area within two miles covers no less than 12.57 square miles. Distance does not tell us in which direction offenders prefer to go. Moreover, most urban landscapes contain a multitude of busy places within a few miles from anywhere.

Therefore, understanding where offenders commit crimes requires more than the two 'stylized facts' about distance decay and crime generators. As emphasized in the opening lines of this article, opportunity theories of crime assert that most crimes are perpetrated during, or are informed by, routine activities pursued without explicit criminal intentions. Thus, to better understand where offenders commit crimes, we need measures to inform us about their whereabouts during their legal daily routine activities.

Unfortunately, systematic information about the places that offenders visit during non-criminal daily routines is not easily available. Only two small-scale studies have addressed the daily mobility of offenders. Rossmo et al. (2012) used data of an electronic monitoring system that tracked continuously in real-time the whereabouts of parolees and offenders on bail under community supervision. Griffiths et al. (2017) used mobile phone data records of terrorists to track their visits to different locations and to examine their visiting frequency distributions in the months preceding the attack they were involved in.

Fortunately, however, the mobility patterns of the general population provide a template for the daily mobility of offenders, and as a direct consequence for their journeys-to-crime (Boivin and D'Elia 2017). The mobility patterns of the population could thus help predict where offenders commit crimes, one of the main aims of this study. We measure the whereabouts of a large fraction of the population of a huge city in China by geo-tracking their mobile phones during a full day. This allows us to measure daily mobility flows of the general population as a proxy measure of the daily mobility of the offender population, and to include this measure as a covariate in a model of crime location choice, together with distance and the presence of crime generators.

Research on crime and law enforcement in China receives increasing scholarly attention internationally. The cultural distance between China and western industrialized countries presents an excellent opportunity to test whether theories developed in western industrialized countries can be generalized to other contexts, in particular China. This opportunity also applies to environmental criminology, because its main theoretical frameworks—routine activity theory and crime pattern theory—have been developed and tested almost exclusively in a western context. A recent exception is a study by Long et al. (2018), who demonstrated that urban street robbers in China tend to return to locations of their prior offences to commit subsequent robberies, confirming prior findings from the United Kingdom and The Netherlands. Another exception is a study showing that Chinese burglars who live in communities with a higher average rent, a denser road network and a higher percentage of local residents, commit burglaries at shorter distances from their homes (Xiao et al.

2018). However, Chinese studies in environmental criminology are still rare, and one of the contributions of the present paper is to add to this developing literature.

In the present paper, we focus exclusively on 'theft from the person' or TFP, a non-violent property offense committed in public or semi-public places, excluding burglaries and thefts from vehicles. Although simple theft is a common crime, it has mostly been ignored in the crime location choice literature.

Research Question

In sum, the main research question of the present study is whether daily mobility flows of the general population, as measured by tracked mobile phone data, help us explain and predict where individual offenders commit thefts from the person. If the answer is positive, an additional question is whether the inclusion of mobility flows adds to the effects of the distance and crime generators, or rather replaces them. In other words, we are interested in the extent to which the effects of mobility flows substitute or complement the effects of distance and of crime generators.

Our findings not only add to the testing and development of opportunity theories, they also contribute to a growing body of research that aims to test in other cultures and on other continents crime theories that have been developed in the USA, Europe and Australia. With its high pace of urbanization and economic, cultural and social change, China seems like an excellent context to test and further develop opportunity theories of crime.

Theory and Prior Findings

The present section will provide a brief overview of the role of distance decay, awareness space and crime generators in the literature on crime location choice. It will subsequently address the potential role of the daily mobility of the urban population in modeling and understanding where offenders commit thefts from the person.

Crime Location Choice

Crime location choice refers to an offender's choice of where to perpetrate a crime (two recent reviews are Bernasco and Ruiter 2014; Ruiter 2017). The discrete spatial choice model was introduced by Bernasco and Nieuwbeerta (2005) as a method to analyze crime location choices using individual-level offender data. The model is rooted in a formal theory of discrete choice known as random utility maximization in micro-economics that is consistent with rational choice as applied to offending criminology (Bernasco et al. 2017b; Cornish and Clarke 1986). The theory asserts that offenders choose crime locations rationally, selecting those locations that maximize their expected rewards and minimize their expected costs and risks. For example, residential burglars would be expected to target accessible areas that are affluent and where formal and informal guardianship is low (Bernasco and Nieuwbeerta 2005), and street robbers would by hypothesized to seek select crime locations nearby their own homes where they are likely to encounter vulnerable victims who carry cash or other valuables (Bernasco et al. 2013). These and other factors assumed to affect crime location choice will be discussed below, in sections "Distance and Awareness Space" to "Mobility Flows", with a special focus of offenders committing theft from the person.

Distance and Awareness Space

Of all factors that affect crime location choices, distance is by far the most influential. All sixteen crime location choice studies reviewed by Ruiter (2017) included a strong and significant negative effect of distance on crime. The theoretical meaning of distance is disputable, as it could be a merely proxy measure for other concepts, such as the cost of travel.

In support of the argument that the time and money costs of travel are more fundamental factors than distance, some studies have demonstrated the crime-reducing effects of physical barriers other than distance. Clare et al. (2009) studied the role of barriers and connectors on destinations chosen by Australian burglars and found them to have a strong influence on offenders' decisions on where to commit burglaries. Peeters and Elffers (2010) assessed the extent to which highways, railroads, parks and canals reduce the number of crime trips across these physical barriers, but found only a small effect. Townsley et al. (2015) demonstrated that for adult offenders, but not for minor offenders, the accessibility of a target via the street network increased its likelihood of becoming a target of theft from a vehicle.

Distance might also be considered a proxy measure of the offenders' awareness space. Because all human mobility, both legal and illegal, displays distance decay, their routine activities help shape their awareness space (Brantingham and Brantingham 2008). Offenders are generally more familiar with places nearby their residence than with more distant places. As a consequence, they must be more knowledgeable of criminal opportunities in nearby places than in distant places. Indeed, some location choice research has suggested that offenders are much more likely to offend within their own awareness space than elsewhere. Arguing that for various reasons offenders might still be familiar with their former areas of residence, it has been demonstrated that they are more likely to offend near their former homes than elsewhere (Bernasco and Kooistra 2010; Lammers et al. 2015; Menting et al. 2016). It has also been established that they are more likely to offend near the homes of family members (Menting et al. 2016).

Offenders may also be familiar with places of prior criminal experiences. They have a tendency to return to places where they previously committed crimes (Bernasco et al. 2015; Lammers et al. 2015), a finding congruent with previous explanations of repeat victimization and near repeat victimization based on victimization data only (Johnson et al. 2007; Townsley et al. 2003).

Establishing a reduced burglary risk in properties along cul-de-sacs, Johnson and Bowers (2010) suggested that their reduced permeability might make cul-the-sacs unfamiliar places for non-residents, including most potential motivated offenders. Frith et al. (2017) use the physical layout of the street network to generate alternative measures of offender spatial awareness, finding the reduced accessibility in the street network reduces the likelihood of street segments being targeted.

In sum, prior research has empirically demonstrated that offenders prefer nearby locations and locations that are part of their awareness space, and thus both proximity and spatial awareness are important criteria in offenders' location choices.

Crime Generators

Crime generators and crime attractors are concepts in crime pattern theory that potentially play an important role in crime location choices. They are facilities that have

elevated levels of crime because they bring together crowds either continuously or at certain moments during the day or the week (Brantingham and Brantingham 1995; Kinney et al. 2008). Crime *generators* are places and facilities where all kinds of people go to perform legal daily activities. Crime *attractors* have been defined as places and facilities that have a reputation of providing opportunities for crime, which makes them particularly attractive to motivated offenders (and unattractive to some potential victims) (Brantingham and Brantingham 1995). Because crime attractors share many features with crime generators, and because the reputational element in their definition may be difficult to evaluate objectively, especially in the context of a non-western culture, in this paper we will subsume crime attractors under the more general label of crime generators.

Although it may be impossible to enumerate all types of facilities that can operate as crime generators, some stand out as being particularly attractive for some types of crime, and they will be discussed in the present section. We describe elements common to certain classes of facility, although even amongst the same class (e.g. bars) there exists considerable heterogeneity making some of them risky places but others not (Eck et al. 2007).

High schools have been associated with elevated crime rates in part because of the assumption that the students are more likely than people of younger or older ages to be involved in crime as offenders or victims. A concentration of adolescents around high schools would possibly generate a concentration of crime before and after school hours (Roncek and Faggiani 1985; Roncek and LoBosco 1983). Near elementary schools, opportunities for TFP are abundant when it is crowded because parents, grandparents and other caretakers drop off the children in the morning, and also when they pick them up later in the afternoon.

Research on street robbery has demonstrated that proximity to small scale businesses, including grocery stores, corner stores, gas stations, barber shops and fast-food restaurants, increases the risk of street robbery (Bernasco and Block 2011; Bernasco et al. 2017a; Haberman and Ratcliffe 2015). To the extent that these are the types of businesses where cash payments are more common than non-cash payment modes, customers may be likely to carry cash. Because street robbery and TFP are similar offenses in terms of location (public space) and preferred items to steal (concealable, removable, available, valuable, enjoyable and disposable, see Clarke 1999; Wellsmith and Burrell 2005), these businesses might also function as crime generators for TFP. For similar reasons, banks and ATMs have been shown to have the same effect (Haberman and Ratcliffe 2015).

The criminogenic effects of bars and other types of alcohol outlets have been demonstrated repeatedly to generate not only violent crimes but also property crime, in particular robbery, and mostly likely because of intoxicated patrons might be easy targets for robbers and thieves (Bernasco and Block 2011; Conrow et al. 2015; Groff 2011; Roncek and Maier 1991).

Especially during rush hours, transit stations (bus stations, subway stations) are crowded places that offer opportunities for theft, in part because travelers may be distracted and not vigilant in their attempts to find the way to their destinations. Many studies have confirmed that crime rates are elevated in and around transit stations (Bernasco and Block 2011; Block and Block 1999; Block and Davis 1996; Clarke et al. 1996; Haberman and Ratcliffe 2015; Qin and Liu 2016).

In sum, the extant literature provides empirical evidence for the fact that locations where people congregate, often in large crowds, are more likely to be selected as crime sites by motivated robbers and thieves. This is particularly true for locations with functions that potentially indicate larger benefits or the presence of vulnerable and non-vigilant victims.

Social Disorganization

Social disorganization has been identified as a community attribute that can apply to geographic areas of various sizes (e.g. street blocks, neighborhoods or districts). Although not a true crime generator (crime generators are facilities with a specific function), it is an observable attribute of communities that attracts offenders, because it provides them with opportunities to offend under the veil of anonymity and with low risks of bystander intervention.

In the extant literature, which mostly covers cities in the United States and in other western industrialized countries, social disorganization is defined as the inability of local communities to realize the common values of their residents or solve commonly experienced problems, such as local crime (Kornhauser 1978), and has theoretically and empirically been associated with concentrated socio-economic disadvantage, residential mobility, and ethnic heterogeneity (Bursik 1988; Sampson et al. 1997). However, in the Chinese context, social disorganization and concentrated disadvantage in cities have been associated primarily with concentrations of non-local migrants (Zhang et al. 2007b), who have recently migrated into the city and lack a *Hukou* status (Hou 2010). Hukou is a household registration system in China that separates locals and 'nonlocals' in the allocation of public resources (Song et al. 2018c). It allows registered individuals—locals, who have *Hukou* status—to apply for public welfare services with respect to housing, education and medical insurance. It is challenging for nonlocals to obtain the *Hukou* status and thereby get access to these welfare facilities, especially for rural workers who have migrated to the city and have experienced segregation from locals, poverty and reduced well-being (Du et al. 2017). Similar to measures of ethnic heterogeneity in the Western case, concentration of 'nonlocal' residents has become an important indicator of social disorganization and crime risk in contemporary research in China (Liu et al. 2018; Zhang et al. 2007b).

Mobility Flows

According to opportunity theories of crime, the mobility of offenders is conditioned by the mobility of the general population (Cohen and Felson 1979). In other words, as offenders move around the city they will generally follow the footsteps of the population and go where everyone else goes (Boivin and D'Elia 2017). Thus, as we argue below, criminal activities and legal activities share some common rules.

Most people who live in urban areas, including offenders, travel on a daily basis in order to pursue activities that are distributed in space, such as work, shopping or leisure. However, the mobility of persons is not random. Instead, people are constrained by certain spatial and temporal conditions (Hägerstrand 1970; Miller 2005). Research in social geography has demonstrated that patterns of mobility are strongly related to personal attributes. Hanson and Hanson (1981) used a transportation survey to study the relationship between socio-demographic characteristics and travel patterns, and found that gender, education, and income affected individual travel patterns. Their findings have been replicated in subsequent research. Schwanen et al. (2008) used activity diaries from 420 adults in 270 households in Columbus (Ohio, USA) and found that women face more constraints on their routine activities than men do. In response to questions about how easily they could change their activities (e.g. laundry, cooking, paid labor) to another location or time of day, women reported their activities to be less flexible than men, both in time and space. Zhou et al. (2015) compared the out-of-home activity spaces of

low and high income groups in Guangzhou (China), and concluded that the segregation between both groups not only applies to where they live, but also to the places and areas they visit during daily routine activities.

Recently, the accessibility of large volumes of geo-referenced mobile phone data has provided researchers with promising opportunities to study daily mobility patterns (Kwan 2016). Song et al. (2010b) used data of phone users and showed daily mobility to be very predictable. Gonzalez et al. (2008) also used tracking data of phone users, and found that human trajectories show a high degree of temporal and spatial regularity, each person being characterized by an individual travel distance and a high probability to return to a few highly frequented locations.

Similar patterns seem to characterize the mobility of offenders. Griffiths et al. (2017) used mobile phone data records of offenders involved in four different UK-based terrorist plots, in the months preceding their attacks. They found that the offenders visited only a very limited number of places, and pursued their activities mainly close to their home or safe house location. This pattern resembles the mobility pattern of the general population. Ratcliffe (2006) demonstrated that spatiotemporal patterns of property crime are strongly influenced by the temporal constraints experienced by the young people who committed these crimes, and that these temporal constraints are very similar to the constraints that non-offenders are subjected to.

These findings are in line with the opportunity theories of crime (Brantingham and Brantingham 2008; Cohen and Felson 1979), which also assert that offenders' crime journeys are not very different from the journeys they make when not perpetrating crimes. This seems not only plausible for crimes that took place in response to unexpected opportunities or provocations, but also for crimes that were premeditated. In case of premeditated crimes, one would expect the offenders to use their pre-existing spatial knowledge to select the target and to escape the crime scene after the offence.

Two studies addressed the relation between the mobility of offenders and the mobility of the general population. Felson and Boivin (2015) formulated a 'funneling hypothesis' asserting that daily mobility flows of an urban population determine where crimes take place. They used a large-scale (N = 165,000) transportation survey to estimate the daily numbers of people visiting each of the 506 neighborhoods of a large city in Eastern Canada for purposes of work, shopping, recreation and education. The volumes of both violent and property crime in a neighborhood were strongly associated with the number of trips (for work, shopping or recreation) having the neighborhood as their destination.

An even more convincing argument is provided by another study that used the same transportation survey in the same study area. Rather than modeling crime volumes per neighborhood, Boivin and D'Elia (2017) modeled the crime trip volumes between all pairs of the 506 neighborhoods (i.e., how many crimes were perpetrated in neighborhood j that were committed by offenders living in neighborhood i, for all 506 i and j). One of their predictors was an estimate of (non-crime) trip volumes between the 506 neighborhoods. Their results indicated that both for violent and property crime and both for crime committed by youths and by adults, the volume on non-crime trips between two neighborhoods was significantly positively associated with the number of crime trips between these two neighborhoods. This finding suggests that the mobility patterns of general population provide a template of 'funnel' for the mobility of offenders, including their journeys-to-crime.

Building on this finding, in the present study we investigate whether, in addition to distance and crime generators, daily mobility flows of the urban population help predict where individual thieves commit crimes. As described in the next section, daily mobility flows are measured using anonymized tracks of mobile phone users in the general population.

Data and Methods

Study Area and Spatial Unit of Analysis

The data for the present research originates from *ZG City*,[1] a city located in southeast China. ZG City has a total population in excess of 5 million, and is one of the largest and most developed cities of China. It belongs to the subtropical zone and the temperature fluctuates between 15 and 32 °C, so there is no extreme cold or hot weather and seasonal variations do not affect mobility.

The study area is located in the central part of ZG City, and covers more than 3000 km^2. The daily mobility pattern of the urban population is a key variable in the present research. Because commuting volumes and distances in China are strongly and positively related to size and prosperity of cities (Engelfriet and Koomen 2017), the choice of ZG city assures that we study a city with a highly mobile population.

The census unit was chosen as the spatial unit of analysis because census units have a size similar to those in comparable studies (Bernasco and Block 2009; Clare et al. 2009; Menting et al. 2016), because census units are approximately equally sized, and because in the study area they are relatively homogenous in terms of population composition. In addition, a practical advantage is that the use of census units does not force us to estimate spillover effects (effects of attributes of nearby units on crime in a focal unit) which is a requirement if small units of analysis are used, such as census blocks or street blocks (Bernasco et al. 2013; Groff and Lockwood 2014).

Using census units as spatial units of analysis implies that we aggregate numbers of crime generators to the census unit level, and thus sum the numbers of schools, restaurants, bus stops and other facilities per census unit. This is not just a practical necessity because all relevant theoretical constructs must be aligned to the same spatial resolution, it is also legitimized by the observation that crime generators produce mobility flows and presence of people in the streets where they are located and in their wider environments.

The size of census units is 1.62 km^2 on average (standard error 2.99 km^2, minimum 0.02 km^2, maximum 31.30 km^2). The mean population is 5956 (standard error 4706, minimum 245, maximum 51,450). The study area comprises 1891 census units in total, of which 275 are not included in the analysis because the lack mobility data due to limited coverage of the GSM mobile phone network, leaving 1616 census units in the analysis. In the section on mobile phone data, we explain why we use census units to locate the cell towers.

Distances between census units are the Euclidian distances in kilometers. For use in the analysis, per offence we calculated the distances between the census unit where the offender lived and all other census units in the study area. Following Menting et al. (2016) and other prior crime location choice studies, the distance to the offender's own census unit of residence was defined as the average distance between two random points in the census unit, which approximately equals half the square root of the size of the area (Ghosh 1951). A total of 595 incidents (17.3%) were committed in the same census unit as where the offenders lived. The average distance of the 3436 crime trips was 5.02 km and their standard deviation is 6.43.

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[1] Access to crime data was granted by the police authorities on the condition that the real name of the city would not be mentioned in publications.

Crime Data: Theft from the Person

Registered crime data were obtained from the police authorities of ZG City. All crime data are recorded incidents of theft from the person (TFP) in which at least one offender was arrested and prosecuted. It includes the date of the incident and the home addresses of the offenders and the location where the offence was committed.

TFP is a very common offence in China and elsewhere. It covers theft and attempted theft of items (e.g. cash, phone) directly from the victim without the use or threat of physical force. TFP includes both snatch theft—in which the victim is aware of the act—as stealth theft—in which the victim is unaware of it (e.g. pickpocketing). TFP does not include thefts with 'break and enter', like residential or commercial burglary, or theft from closed vehicles. Theft from the person targets people rather than buildings, vehicles or other objects. It is therefore a very appropriate crime type to explore the relation between the mobility of the general population and the target choice of offenders.

Because the home location of the offender is an essential element of the model, the data used in this study contain only detected cases, i.e. cases where a suspect was arrested, identified and prosecuted. The clearance rate of theft from the person in ZG City was 5.2% in 2014, which implies that approximately 1 in every 20 thefts leads to the arrest of an offender.

In the original dataset, there were 10,276 cases of TFP committed by 12,670 offenders between June 1st, 2014 and May 30th 2016. The month of February in both 2015 and 2016 was excluded, because during this the Chinese Spring Festival takes place, and a large proportion of the population leaves ZG city to celebrate the lunar new year with their families in their hometowns. This temporary change might alter the regular mobility patterns of both offenders and potential victims.

Because data on the daily mobility patterns of the urban population was only available on weekdays, only TFPs on weekdays were selected for the analysis. Unfortunately, as in many other studies (e.g., Vandeviver et al. 2015) a substantive percentage of cases had to be excluded from the analysis for lack of geographic detail. In 6118 cases either no offender address or no TFP location was available. After selections, the remaining 4019 offences committed on weekdays and with valid location information were committed by 4798 offenders in total. The fact that offenders outnumber offences implies that some TFPs are committed by co-offending groups.[2] Because estimation results might be biased if offences committed by multiple co-offenders would incorrectly be analyzed as if they were independent observations, and in line with recommendations in the crime location choice literature (Bernasco and Nieuwbeerta 2005; Townsley et al. 2015) only solitary offending was selected for inclusion in the analysis,[3] leaving for the analysis 3436 cases of TFP.[4]

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[2] Of the 4798 TFP offenders, 4730 (98.6%) were involved in a single TFP, 55 were involved in 2 TFPs, 6 were involved in 3 TFPs, 5 in 4 TFPs, 1 in 5 TFPs and another 1 was involved in 17 TFPs.

[3] Of the 4019 TFPs, 3436 (85.0%) were committed by a single offender, 423 (10.5%) where committed by two offenders, and 92 (2.3%) were committed by three offenders. The remaining TFPs were committed by offender groups of sizes 4–10.

[4] By way of robustness check we also estimated an alternative, in which only a single offender was selected randomly from a co-offending group, and including in the analysis. The resulting estimates were very similar to those on solitary offenders reported here, and can be obtained from the authors.

Crime Generators

The list of potential crime generators is sheer endless, but included are those facilities that seem most relevant based on the extant literature and taking into account the Chinese context: the numbers of primary schools, middle schools, hospitals, basic stores, markets, supermarkets, restaurants, cinemas, bars, banks, subway stations and bus stops per census unit. All of them are so-called 'point of interests' (POIs) that were purchased from Daodaotong, a mapping and navigation company, which provides the original map data for China's largest search engine (Zheng and Zhou 2017). These POIs in ZG city were collected in 2014.

Primary schools include kindergartens and elementary schools. Potential TFP victims are not the pupils but the adults (usually parents or grandparents) who gather near the gates of schools around the school exit hour to pick up their children. Most middle school students are not picked up by their parents and would be potential TFP victims themselves, as the middle schools are also very crowded at school exit hours, creating opportunities for TFP. As presented in the descriptive statistics in Table 1, there are 1.28 primary schools and 0.36 middle schools on average per census unit.

Hospitals refer to general hospitals, which in China are always busy places. Basic stores include shops for daily supplements and for clothes. With an average of 5.22 per census unit they are quite common. Markets comprise open air markets as well as 'integrated markets' that mainly sell food. Banks include both banking business offices and automated teller machines (ATMs). Restaurants, cinemas and bars are popular entertainment facilities that attract crowds, and subway stations and bus stops attract large volumes of people who are in transit. As for public transportation, each census unit has 3.19 bus stops but only 0.07 subway stations on average.

In addition to counting crime generators that are facilities, we also calculated the population heterogeneity for each census tract. In the Chinese context, segregation does not follow racial or ethnic lines as they do in many western countries. In Chinese cities, the main attribute that distinguishes locals from non-locals is their *Hukou* status. Non-local communities where few residents have local Hukou status are generally characterized by high levels of anonymity, weak social attachments among residents and serious social disorder problems. Across all census units the mean proportion of non-locals is 0.34.

Table 1 also contains a correlation matrix of the crime generator variables. The correlations between the crime generator counts are low. The only one stronger than 0.50 is the correlation between the number of restaurants and the number of supermarkets. As a consequence, there is no reason for concern about collinearity issues.

Mobile Phone Data

To measure population mobility across the study area, we use the tracked data of mobile phone users. There is a burgeoning literature using mobile phone location tracking to study the movement patterns and travel behavior of human populations (Asakura and Iryo 2007; Yang et al. 2014). An advantage of mobile phone data over transportation surveys is that mobile phone data are not forced into a specific origin–destination format that restricts the measurement to start and end locations. Mobile phones monitor the location of the population continuously without assuming origins, destinations or intentionality. Another advantage is that the measures are taken automatically and unobtrusively and do not require active participation of research subjects.

Table 1 Descriptive statistics and correlations of census unit characteristics (counts of crime generators and % nonlocals)

	Mean	SD	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13
Primary schools	1.280	1.321	0	8	1												
Middle schools	0.357	0.732	0	5	0.208*	1											
Hospitals	0.216	0.551	0	4	0.072*	0.113*	1										
Basics stores	5.224	18.111	0	313	0.086*	0.045	0.102*	1									
Markets	0.368	0.695	0	8	0.243*	0.092*	0.080*	0.079*	1								
Supermarkets	1.530	2.640	0	25	0.362*	0.140*	0.034*	0.148*	0.307*	1							
Restaurants	11.152	13.835	0	122	0.396*	0.253*	0.139*	0.322*	0.280*	0.544*	1						
Cinemas	0.036	0.196	0	2	0.004	0.018	-0.015	0.237*	0.021	0.034	0.120*	1					
Bars	0.193	0.666	0	11	0.140*	0.029	0.126*	0.105*	0.070*	0.052*	0.324*	0.051*	1				
Banks	1.835	2.724	0	42	0.217*	0.142*	0.111*	0.247*	0.140*	0.209*	0.448*	0.140*	0.224*	1			
Subway stations	0.074	0.285	0	3	0.007	0.033	0.012	0.038	0.062*	0.032	0.141*	0.119*	0.052*	0.281*	1		
Bus stops	3.188	4.605	0	102	0.297*	0.191*	0.081*	0.084*	0.150*	0.406*	0.428*	0.100*	0.080*	0.291*	0.142*	1	
Non-locals (%)	0.340	0.236	0	0.974	0.217*	0.070*	-0.022	0.096*	0.261*	0.460*	0.319*	-0.006	-0.02	0.098*	-0.019	0.266*	1

SD standard deviation

*$p < 0.05$ (two-sided)

The data of the locations of mobile phone users in this research was provided by a major mobile phone service provider in China that has a market share of 22.5% (Chong et al. 2015). Song et al. (2018a) used the mobile phone users' data from the same provider to measure ambient populations, and argued that there are no major systematic differences between the customers of different mobile phone providers, which suggest that our sample of mobile phone users is representative for the general population in ZG City. Like Xu et al. (2016) using mobile phone data of 1 day to measure activities, our mobile phone data contains tracking information of the routes taken by the mobile phones on the network hour by hour on Wednesday, December 28, 2016, a fairly regular day in ZG city.

In this single day, there were 2994 million users for whom a total of 30,632 million locations were recorded by the telecom provider. Note that cellular signaling data involves any behavior that creates a relation with the cell signal tower, such as Internet search, messaging and voice calls. Multiple times per minute the 4G phone network determines which of its phone towers is nearest to the mobile phone, if the phone is being used.

The tracking points are location estimates based on the census units where the phone towers are located that provide network communication services. The reception area of a tower varies from as little as a few meters in central area to a few kilometers in suburban areas, resulting in some uncertainty about the user's precise location (Song et al. 2010a).

In ZG city, the distribution of towers is of high density. The mean distance of a tower to the nearest tower is 136.4 meters, with a standard deviance of 255.8 (Min: 0.0; Max: 5535.1; 50%: 48.3 m; 75%: 137.6 m; 95%: 589.4 m). The average size of the 1616 census units is 1.62 km^2. It can be deducted that most of the service area of the cell tower is located within one census unit. Therefore, it seems acceptable to allocate the locations of cell phones to the census units where the tower is located that they are connecting to.

To protect the privacy of the mobile phone users, the telecom company gave us access to an aggregated dataset that did not include all measured location points.[5] Instead, it includes for each mobile phone and for each hour, the location of the cell tower that has been the nearest tower most of the time during that hour. For example, if between 2 pm and 3 pm a mobile phone has been near tower A for 20 min, near tower B for 30 min and near tower C for 10 min, the estimated location between 2 pm and 3 pm is the location of tower B.

The aggregated dataset contains for each user 10.2 cell tower hours/locations on average. Half of the users had more than 7 h/locations. During the remaining hours, the phone users were either sleeping, performing activities during which they did not use their phone (e.g., work, school, travel) or moving outside the areas covered by the network. Although an average number of just over 10 space–time measures per respondent may appear to be a sparse measure of mobility, it probably implies that the recorded locations are places where the phone users spend nontrivial amounts of time and therefore correspond to meaningful activity nodes. Moreover, an average of 10 locations may cover most of the phone users' activity spaces. According to empirical findings on human mobility based mobile phone trajectories, humans have a strong tendency to return to places they visited before. At any point in time, the number of familiar locations an individual visits is limited to approximately 25 locations (Alessandretti et al. 2018), and they spend more than 80% of their time in their 10 most frequented locations (Gonzalez et al. 2008; Song et al. 2010a). In a subsequent aggregation procedure that we ourselves implemented, each phone tower location was assigned to the census unit in which it was located. The result is a data file that

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[5] Even at this level of spatial resolution, only four spatio-temporal points are enough to uniquely identify 95% of the phone users (Montjoye et al. 2013).

records for each mobile phone user and per hour in which of the 1616 census units they were located.

Calculation of Mobility Streams

The resulting information was subsequently used to construct a measure of the volume of mobility flows between all pairs of census units. The measure is defined as the number of unique mobile phone users that visited both census units on the same day. Mobility flows were calculated by summing phone users over all pairs of census units. The result is a square matrix of census units containing the number of mobile phone users that visited both census units on a single day.

Our use of mobile phone locations diverges from how prior studies on crime in London (Bogomolov et al. 2014) and in Osaka, Japan (Hanaoka 2018) have used such data in research on crime. These prior studies used mobile phone users' locations as a measure of how many people were present at a specific location at a specific day or time, which has been referred to as the size of the ambient population or the actual population at risk. Other studies have measured the ambient population with other data sources, such as the Landscan Global Population database (Andresen 2006; Andresen and Jenion 2010), geo-references Twitter messages (Malleson and Andresen 2015), or public transportation transaction data (Song et al. 2018b). Our measure is different from measures of ambient population because it measures how many people visit two different locations during a single day. It thus measures mobility, not just presence.

By linking all census units where a specific mobile phone was observed during the day, we construct a measure of observed mobility between pairs of census units: the mobility between census units A and B is the number of mobile phone users visiting both census unit A and census unit B on the same day (irrespective of how frequent and how long the visits are). The average across all pairs of census units is 466 individuals, with a standard deviation of 16.54. In the analyses, we only use pairs in which at least one of the census units included the home location of a TFP offender, and therefore all other pairs are discarded. Although the distribution is positively skewed, the number of pairs with a zero mobility flow is limited. Almost half (47.7%) of the $0.5 \times 1616 \times 1615 \approx 1.3$ million census unit pairs had a zero mobility flow (meaning that nobody of the 2.9 million users visited both locations on the same day). For those pairs that were included in the analysis (because they included at least one offender's census unit of residence), this percentage was 37.7%.

Finally, to arrive at a measure that could represent the likelihood of an offender living in census unit A to offend in census unit B, we define the relative mobility between A and B. The relative mobility is a percentage calculated as the ratio of the mobility flow and the total number of mobile phone users visiting the home census unit of the offender on a single day (also irrespective of frequency and duration), and multiplying the result by 100. It is hypothesized that the probability of an offender living in area A will offend in area B is proportional to the percentage of visitors to A who also visited B (the relative mobility flow from B to A is therefore different form the relative mobility flow from A to B). By using the relative measure we standardize for the total number of people visiting the census units
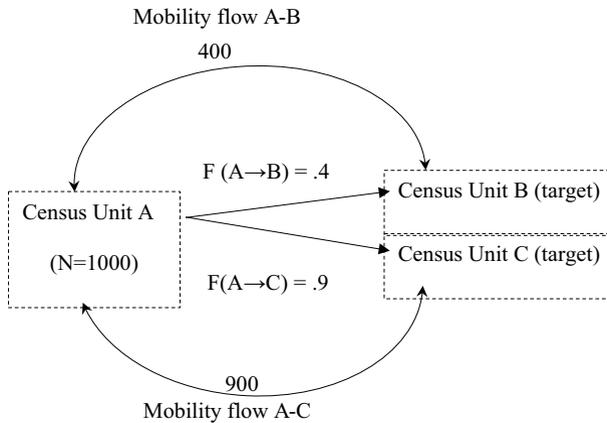
Fig. 1 Conceptual model of relative mobility flow with a numerical example. $F(A \rightarrow B)$ is defined as number of people visiting both A and B on the same day (400), divided by the total number visiting A on the same day (N = 1000). $F(A \rightarrow C) = 900/1000 = 0.9$. F $F(A \rightarrow A) = 1$

where the offenders live.[6] A stylized example is shown in Fig. 1. Suppose that an offender lives in census unit A and there are only two other locations, census units B and C. Our aim is to assess whether the relative mobility between census units A and B and the relative mobility between census units A and C impact the probability of the offender selecting either census unit B or C, and our best guess is that these location choice probabilities are proportional to the relative mobility flows, i.e. to 400/1000 and 900/1000 respectively. It should be emphasized that the mobility between two census units (for example A and C) does not mean that the mobile phone users must live in either census unit A or census unit C. They can also be two of the users' other activity nodes.

In the models, to account for the fact that the distributions of both distance and relative mobility are positively skewed, their logarithms are taken (after adding a value of 1 to the relative mobility to prevent taking the undefined logarithm of 0).

As most human mobility is over short distances and the frequency of trips decreases with distance (Gonzalez et al. 2008), we should expect the volume of mobility between census units to be inversely related to their distance. This is indeed the case, although the correlation is far from perfect: after taking logarithms it is −0.37.

Models

Following the large majority of previous location choice studies, we used the conditional logit model to analyze the role of distance, crime generators and daily population mobility in the offenders' choice of locations for committing TFP. The conditional logit model is easy to estimate and consistent with random utility maximization theory (McFadden 1973). As Bernasco (2010) provided a fairly extensive treatment of the model in the context of

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[6] Empirically, models including (the logarithm of) the absolute mobility flow as a covariate yielded very similar results as models (the logarithm of) the relative mobility flow. Conceptually, the relative measure is superior as it accounts for the 'centrality' of the offender's census unit of residence.

crime location choice, here we confine ourselves to a brief summary, using terms that fit our application to TFP in ZG City.

According to the model, a decision-maker i (the TFP offender) choses a single alternative n (a census unit) from a set of 1616 mutually exclusive alternatives (census units). The offender determines the level of utility U_{in} that he or she would derive from targeting each potential census unit, and chooses the census unit that will provide most utility. The utility level U_{in} is a linear function of the characteristics of the census units (or their logarithms):

$$U_{in} = \beta_D \log(D_{in}) + \beta_F \log(F_{in}) + \boldsymbol{\beta_X X_n} + \varepsilon_{in}$$

where U_{in} is the utility that offender i would derive from census unit n, D_{in} is the distance between the home census unit of offender i and census unit n, F_{in} is the relative mobility flow between the home census unit of offender i and census unit n, and $\boldsymbol{X_n}$ is a matrix representing the other characteristics of the census units (number of primary schools, number of bus stops, etc.). The β_D, β_F, and $\boldsymbol{\beta_X}$ are the parameters associated with the logarithm of distance, the logarithm of relative mobility flow, and the other variables in the equation, respectively. They are estimated based on the actual location choices observed, and their estimated values indicate the impact of the characteristics on the outcome of the offender's location decision. The term ε_{in} is an error term that reflects unmeasured other choice criteria affecting U_{in}. If the error term is Extreme Value Type II distributed, it can be derived that the probability that offender i chooses census unit n equals:

$$P_{in} = \frac{e^{\beta_D \log(D_{in}) + \beta_F \log(F_{in}) + \boldsymbol{\beta_X X_n}}}{\sum_{j=1}^{1,616} e^{\beta_D \log(D_{jn}) + \beta_F \log(F_{jn}) + \boldsymbol{\beta_X X_n}}}$$

In presenting our results, we include the estimated coefficients expressed as odds ratios (i.e., transformed into e^β), the corresponding z-value and an indicator of the level of statistical significance of the coefficients. The independent variables haven't been standardized because the unstandardized results are easier to interpret and because the aim is not to compare effect sizes across the independent variables. We present the results of two alternative models. The first model includes the distance as well as the crime generators, but not the mobility measure derived from the mobile phone locations. The second model is identical to the first model, but with the mobility measure included.

The estimated coefficients are most easily interpreted when they are transformed into odds ratios (ORs). ORs with values between 0 and 1 indicate negative effects: a one-unit increase in the independent variable (e.g. number of bus stops) decreases the odds of victimization by a factor equal to the OR. OR values above 1 represent positive effects: a one-unit increase in the independent variable increases the odds by a factor equal to the OR. To judge relative fit between multiple models, we use MdFadden's Pseudo R^2, the Akaike's information criterion (AIC) and the Bayesian information criterion (BIC) as benchmarks. Larger values of the Pseudo R^2 and smaller values of the AIC and the BIC indicate better model fits.

Findings

In Table 2 we present the estimation results of the two models. In Model 1, the presence of schools, markets and bars is not significant. All other facilities, appear to function as crime generators. This also applies to the proportion of nonlocal residents, which we assume

Table 2 Results of conditional logit model of the choice of census unit to commit theft from the person

Variables	Model 1		Model 2	
	Odds ratio	z	Odds ratio	z
Crime generators				
Primary school	1.002	0.110	0.993	− 0.450
Middle school	0.961	− 1.670	0.959	− 1.750
Hospital	1.135***	4.430	1.125***	4.030
Basics stores	1.004***	6.340	1.004***	6.590
Market	1.055*	2.510	1.039	1.730
Supermarket	1.027***	5.310	1.025***	4.750
Restaurant	1.018***	14.540	1.016***	12.980
Cinema	1.154*	2.020	1.149	1.940
Bar	1.008	0.360	1.014	0.690
Bank	1.031***	8.200	1.030***	7.780
Subway station	1.570***	10.340	1.565***	10.120
Bus stop	1.031***	19.580	1.029***	17.410
Social disorganization				
Nonlocal proportion	1.198*	2.020	1.138	1.430
Distance (ln(km))	0.178***	− 117.040	0.217***	− 69.470
Relative Mobility flow(ln)	–	–	1.292***	11.040
Model information				
Pseudo R^2	0.298		0.301	
AIC	35,649.27		35,512.87	
BIC	35,838.69		35,715.81	
# Observations (TFPs×census units)	5,552,576		5,552,576	
# Thefts from the person (TFPs)	3436		3436	
# Census units	1616		1616	

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$ (two-tailed, based on robust standard errors)

reflects a relative social disorganization that increases the risk of being targeted by the TFP offenders. As all other estimates are significant and have values above 1, the presence of these facilities in a census unit significantly increases the likelihood that it is selected for committing a TFP.

Subway stations, cinemas and hospitals are large-scale facilities and also seem to have the largest effects: with one more subway station, cinema or hospital in the census unit, the odds of being chosen increases by 57.0, 15.4 and 13.5% respectively. In terms of effect size, the other facilities (basic stores, restaurants, bars and bus stops) are less influential, which must be related to their smaller scales. A one-unit increase in the proportion of non-locals in the census units (being the difference between nobody being non-local and everybody being nonlocal) increases the odds of the unit being targeted by 19.8%. Proximity (the logarithm of distance) has a very strong positive effect on the offender's choice of a target area: the closer to the offender's home, the more likely a census unit is to be chosen as a crime site.

Model 2 extends Model 1 by taking into account the population mobility between census units. In line with the hypothesis, the odds that an offender selects a census

Table 3 Pseudo R^2 of conditional logit models with (1) crime generators only, (2) relative mobility flows only and (3) distance only, (4) distance and relative mobility flow, 3436 thefts from the person and 1616 census units

Model	(1) Crime generators and social disorganization	(2) Relative mobility flow (ln) only	(3) Distance (ln) only	(4) Distance (ln) and relative mobility flow (ln)
Pseudo R^2	0.045	0.193	0.260	0.270
AIC	48,518.13	40,998.54	37,554.39	37,044.98
BIC	48,694.02	41,012.07	37,567.92	37,072.04

unit as a crime location significantly increases with the strength of mobility between this census unit and his or her own census unit. The finding suggests that the mobility volume does indeed reflect offenders' whereabouts. We expected that the inclusion of population mobility would capture a considerable proportion of the legal and illegal whereabouts of offenders, and thereby attenuate the effect of distance. Indeed, the inclusion of the mobility measure does reduce the effect of distance, as it is weaker in Model 2 (odds ratio = 0.217) than in Model 1 (odds ratio = 0.178). The attenuation is limited, however, and distance remains an important predictor of location choice in its own right.

The inclusion of population mobility flow hardly affects the values and significance levels of the other estimates, as they are similar in Models 1 and 2. The main changes are that the effects of the presence of markets, cinemas and the proportion of nonlocals are smaller and lose significance in Model 2.

In terms of the model fit, the improvement is not that significant. Pseudo R^2 of Model 2 is 0.301, which is within rounding error of the Pseudo R^2 value of 0.298 observed in Model 1. However, with decreases larger than 120, the differences in both the AIC and the BIC from Model 1 to Model 2 are significant,.

As shown in Table 3, we further estimated four more parsimonious models to test how each of the theoretical constructs—crime generators and social disorganization, distance, mobility flows, and the combination of distance and mobility flows—would predict TFP locations in isolation of the other constructs in Table 2. The values of Pseudo R^2, AIC and BIC show that in terms of model fit, distance outperforms mobility flow, but both distance and mobility flow fare much better than crime generators. In other words, knowing the census units of all crime generators in ZG City hardly helps us predict where an individual offender will perpetrate a TFP, while knowing the locations in ZG City visited by people who also visited the offender's census unit of residence provides a much better prediction. According to the R^2 criterion, however, distance still generates the best prediction. Although statistically significant, the addition of mobility only marginally improves model fit.

Conclusion and Discussion

Routine activity theory and crime pattern theory are opportunity theories of crime. Their key assumption is that crime feeds on legal activities, either because offenders encounter unforeseen criminal opportunities while engaged in legal routine activities, or because their routine activities inform them about criminal opportunities that they exploit at a later point in time.

The present study was inspired by this assumption. Its purpose was to explore whether knowledge of the daily mobility pattern of the population across urban space furthers the explanation of where offenders choose to commit thefts from the person.

Based on unobtrusively recorded locations of anonymized mobile phones of a large proportion of the population, we created a mobility matrix between all pairs of the 1616 census units in a large city in China, and demonstrated that, after accounting for distance and the presence of crime generators, offenders were indeed more likely to offend in census units with large mobility flows connected to their area of residence.

This finding provides support for opportunity theories of crime, as it suggests that to a considerable degree the 'journey-to-crime' follows the mobility of the general population. An offender living in a particular area will commit crime in a target area with a probability that is proportional to the relative mobility of the population between the two areas, i.e. to the number of people that visit both areas as a percentage of those visiting his or her home area. However, theoretically, it should be emphasized that the mobility flow measure in itself does not add a new element to the crime equation. It should be interpreted as a useful correction on the estimated effects of distance and crime generators. In the next paragraph we explain why.

Distance is an imperfect measure of the friction that constrains the mobility between two locations. Greater distance reduces mobility, but there are more factors affecting the friction between locations. In addition to distance, physical barriers (such as rivers and railroad tracks) and social barriers (such as cultural and language differences between the two locations) may further increase these constraints, while connectors (like high-speed trains, cultural similarity or a shared language) may reduce it. Because our mobility measure based on mobile phone locations represents actual mobility, it could easily pick up some of the variation created by barriers and connectors that are not captured by distance. Furthermore, with travel distance fixed, the mobility measure did contribute to explaining where offenders went to commit TFP.

With regard to crime generators, a similar issue of unobserved heterogeneity arises, because it is likely that in our analysis we missed some facilities that function as crime generators, such as beaches, sport stadiums or city parks. In addition, we may have missed some variability within the same crime generator category (e.g., some bars may be more 'risky' than other bars, see Eck et al. 2007). If we did miss some types of crime generators, or if we missed some variability within a single crime generator category, the mobility measure is likely to capture this omission by attributing the effect of this facilitator to the mobility measure. From the comparison between the effects it appears that in the prediction of theft from the person, the mobility measure performs much better than the presence of crime generators.

The fact that mobility can easily pick up effects of omitted variables made us expect that the inclusion of mobility would significantly reduce the independent effect of distance. As a matter of fact, we would not have been surprised to see the mobility measure completely take over the distance effect. This expectation is not confirmed, however,

because the effect of distance remains dominant even after including mobility flows in the equation. This finding may suggest that even within their activity space, thieves still have a preference for relatively nearby targets. It might also be a signal that the mobility of the general population does not perfectly align with the mobility of the offender population. Possibly, some or most offenders have routine activities and spatial patterns that are different from those of non-offenders. In particular, their daily mobility patterns might be more spatially constrained than those of the general population, as this could also explain why the effect of distance remains dominant even after including the mobility measure in the equation. Therefore, our findings provide a specific interpretation of the claim of routine activity theory that "illegal activities feed upon the legal activities of everyday life". Our findings suggest that illegal activities do indeed feed upon the legal activities of the general population, but also that offenders are more constrained by their limited action radius than other members of the population.

Core variable estimates like those of distance and most crime generators seem to function in line with what we know from other studies (Ruiter 2017). Distance is the key factor that prevents offenders from selecting targets away from their homes, and the presence of crime generators is the key factor that attracts crime. Furthermore, in terms of model fit, the Pseudo R^2 of our models is just around 0.30, a value that is comparable to the ones reported in other studies of crime location choices.

Nevertheless, there are also some differences with results of the effects of crime generators reported in the literature. Elsewhere, the presence of high schools has been shown attract offenders in cases of robbery and theft from vehicle (Bernasco and Block 2009; Townsley et al. 2015) while our results indicate the opposite for TFP. It is not immediately clear whether the cultural context, the type of crime or other factors explain this discrepancy. One possible explanation is that Chinese schools tend to be tightly managed (with entry controls) and most require students to wear uniforms, making them less attractive than the schools in U.S.A and other Western countries. Bars do not seem to impact TFP crime location choices. A likely reason is that bars are not as popular in China as they are in Western countries, and few Chinese would consider going to bars for leisure. The proportion of nonlocals is a special measure that specifically applies to the Chinese social environment. It does not seem to be a major importance for TFP location choices.

As any study, ours is limited in various ways, and some caveats must be made. First, our analysis ignores temporal variation. We did not include the timing of thefts from the person or the timing of population mobility flows. Neither did we take into account variation in opening hours of facilities during the day. In future work, the inclusion of temporal variation in both crime and population mobility will provide a better testbed for opportunity theories, because it allows researchers not only to verify that crimes are more likely to happen at certain time of the day, but also to test whether location choices of theft from the person are driven by the same choice criteria in the morning as in the evening (van Sleeuwen et al. 2018). Because mobile phone activity logs include time stamps that tell us not only where people are, but also when they are there, population mobility flows can also be distinguished by time of day. In fact, a next generation of research could add time use data collected with surveys (Haberman and Ratcliffe 2015) or with smartphone apps (Ruiter and Bernasco 2018) to enrich the available data by measuring what type of activity individuals are involved in (e.g. traveling, working, shopping), presumably affecting their victimization risk.

Second, we did not explore any differences between co-offending and single offending. The members of co-offending groups were excluded from the analysis, as they may live in

different communities, and therefore their spatial decisions are much more complex than those of solitary offenders (see Lammers 2017).

Third, only the data of 4G users of one mobile phone network provider is available in our research. Although the 4G network is very popular in China, the sample of users whose phones were tracked may not be fully representative of the population of ZG City.

Fourth, only theft from the person was studied here. This is a 'street' crime characterized by a low rate of reporting to the police (Zhang et al. 2007a). To what extent population mobility flows impact the spatial behavior of those who commit other types of crimes, including crimes against static targets, such as burglary, remains an open question. The approach adopted here, in particular the use of cell phone data to measure population mobility, might prove useful in in future research that addresses this question.

The abovementioned caveats should not dwarf the contributions of the present study. In addition to applying a new mobility measure based on tracking the locations of individual cell phones, this study contains two other new elements to the discrete crime location choice framework. It has been the first to apply the framework in the Chinese context, and it has been the first to apply it to theft from the person. The findings demonstrate that Chinese offenders committing theft from the person decide on target areas in ways that resemble the choices made by burglars and robbers and other types of offenders elsewhere in the world. This may be viewed as tentative evidence that the underlying opportunity theory could be applicable not only in the industrialized world, but also in other countries.

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