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Ambient population and surveillance cameras: The guardianship role in street robbers' crime location choice

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ABSTRACT

Understanding how offenders choose a crime location is a classic criminological topic. However, previous research on offenders' crime location choice did not consider the impacts of ambient population and surveillance cameras on street robbery. Based on the literature, this study integrates ambient population and surveillance cameras data, from the perspective of guardianship. The discrete spatial choice modeling is used to test the impact of their guardianship role on street robbers' crime location choice, accounting for accessibility and proximity, crime attractors and generators, and social disorganization. The results demonstrate that ambient population and surveillance cameras have a significant hindering impact on street robbers' crime location choice, and they play a guardianship role in street robbers' criminal activities. In particular, we find that the guardianship effect of ambient population is greater than that of surveillance cameras. Further, the inclusion of ambient population and surveillance cameras increases the fitness of the model, which underscores the guardianship role of these two factors on street robbers' choice of location on committing a robbery. These findings can have important implications for the role of the ambient population and the deployment of surveillance cameras for crime reduction.

1. Introduction

Street robbery is extremely harmful to society due to its serious impacts on public safety and lifestyle. Street robbers intimidate or use violence to obtain the property of victims, usually attacking victims by surprise with or without a weapon. They lurk in a certain place waiting for a suitable target to appear or follow the target to a location where they feel safe to attack and escape. Robberies can cause psychological trauma to victims and their families (Angel et al., 2014; Gale & Coupe, 2005). The public fear of street robberies (Cook, 2009) affects residents' daily activities such as work, shopping, travel, and leisure (Cook & Ludwig, 2000; Gialopsos & Carter, 2015). For example, Cohen et al. (1981) believed that in 1960s and 1970s in the USA, robbery caused panic among American citizens. Many residents in the city center stay at home, while others fled to the suburbs (Silberman, 1978). Conklin (1972) speculated on why robbery evoked such a stronger response (anxiety caused by robbery) in urban public areas than other types of crime, and suggested that this was because robbery was usually committed by strangers with unexpected violence. The unpredictability of robbery makes it more threatening. Thus, potential victims avoid exposing themselves to dangerous places, whereas potential robbers do the opposite. If possible, potential victims will choose to shop or work in places where they are not worried about being robbed (Bernasco et al., 2013). In sum, street robbery is a street crime that people are most concerned with (Bernasco et al., 2013).

A key research question is how the built environment and social environment affect individual offenders, and the specific process and response mechanism of their crime location choice preferences (Ackerman & Murray, 2004; Levy, 2009; Newman, 1996; Sampson et al., 1997). Bernasco et al. (2013) demonstrated that Chicago street robbers attack near their own homes and on easily accessible blocks. The smaller the physical distance to the street robber's residence and the smaller the

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social distance to the street robber's racial or ethnic background is, the higher the likelihood of street robbery. Townsley et al. (2016) investigated the crime location choice by a sample of residential burglars in Brisbane, Australia, and they found that burglars' crime location choice was affected by neighborhood affluence, the number of households, percentage single-family dwelling, the accessibility of potential targets, and the proximity to city center. Taking the ZH peninsula of ZG City in China as an example, Long, Liu, Feng, et al. (2017) used the partial least square method to test the impacts of built environment and social environment on crime location choice of burglary and outdoor theft at the neighborhood scale, and found that the impacts vary by crime type. Additionally, He et al. (2017) use Google Street View to study the relationship between violent crime and physical features of an urban residential environment.

China's rapid urbanization has attracted people to cities, and the increased population has led to more crime. Half of the population in large coastal cities are domestic migrants, which are also called floating population. Surveillance cameras are prevalent in Chinese cities, to help fight crime and maintain social order. During the past 10 years, empirical crime research has drawn tremendous attention in China, with crime location choice being an emerging theme. Previous research on offenders' crime location choice did not consider the impacts of ambient population and surveillance cameras on street robbery. To fill this gap, this study integrates ambient population and surveillance cameras in assessing street robbers' decision making in ZG City of China, by using discrete spatial choice modeling.

2. Related research

Research on offender's crime location choice is often guided by routine activity theory, crime pattern theory, and social disorder theory. In addition to crime attractors and generators, accessibility and proximity, and social disorganization, this research focus on the potential impact of ambient population, surveillance cameras. The following paragraphs provide a brief review of the related research.

2.1. Ambient population

Residential population data or census data are frequently used to link the crime rate of an area with the number of residents to estimate potential risk (Mburu & Helbich, 2016). The patterns of human mobility cause shifts in the baseline population, which may potentially affect crime analysis (Mburu & Helbich, 2016). Travel surveys, activity surveys, and workday census surveys have been used to overcome the limitation of residential population, but they are often limited in spatial coverage and spatial resolution (He et al., 2020).

Recently, the availability of large volumes of geo-referenced diverse data sources has provided researchers with valuable opportunities to study human mobility patterns (Kwan, 2016). For example, big data generated from social media data, mobile phone data, remote sensing dataset, bus and metro smart card data have been used to generate ambient population (Andresen, 2011; Hanaoka, 2016; Hipp et al., 2019; Malleson & Andresen, 2015; Song et al., 2018; Song et al., 2019). To date, there is a growing literature that uses mobile phone data to measure the presence of people in the landscape. In particular, mobile phone data have wide spatial coverage and temporal continuity (Panigutti et al., 2017), so data generated by communication tools such as mobile phones now provide promising opportunities to explore the spatiotemporal patterns of human mobility and social behavior (Vespignani, 2009). For instance, Song et al. (2018) believe that due to the widespread adoption and use of mobile phones and the normal operation of their geolocation function, the utilization of location data from mobile phones seems more promising. In line with Song's view, Feng et al. (2019) consider that most people carry mobile phones in their daily lives, so it's reliable to calculate ambient population from mobile phone data with a higher spatiotemporal resolution.

Additionally, the ambient population is used to measure the population at risk of crime (Andresen & Jenion, 2010). In particular, a few recent studies have found that ambient population has a positive (or negative) impact on offender's crime location choice. For example, the study of theft by Song et al. (2019) found that the increase in ambient population amounts to more potential victims (risk population). By contrast, Boivin (2018) research suggested that the relationship between burglary location choices and ambient populations was negative. The contrasting effects between the study of Song et al. (2019) and that of Boivin (2018) are not really surprising. Many studies (Ackerman & Rossmo, 2015; Andresen et al., 2016) demonstrated that disaggregated crime types have different spatial and temporal patterns. Groff and Lockwood (2014) found that the impacts of environmental factors vary across crime types. This paper adds to the literature in testing whether the ambient population generated by mobile phones affects street robbers' crime location choice.

In sum, an increased human presence in a given area is expected to be associated with both an increase and a decrease in criminal activity, depending on the nature of crime (Boivin, 2018). Ambient population may act as guardians by their simple presence (Felson & Eckert, 2015), thus deterring crime. Conversely, ambient population act as the target, thus increasing crime (Song et al., 2018). For street robbery, it is unclear whether the increase of ambient population means more guardianship role, especially in the context of offenders' location choice.

2.2. Surveillance cameras

Many studies have investigated the impact on crime by various proactive policing tactics, such as foot patrol, hotspot patrol, problem-oriented policing, and offender-focused policing, as well as security equipment such as surveillance cameras (or closed-circuit television, CCTV), intrusion alarm system, etc. With a focus on small places or groups of people in small places, they worked out specific solutions by using careful analysis of local conditions that seem to act as a deterrent to stop offender' criminal behaviors, thus becoming effective at reducing crime (Groff et al., 2015; Kubrin et al., 2010; Long et al., 2018; Reid & Andresen, 2014; Sampson & Cohen, 1988).

Surveillance cameras (or CCTV) may strengthen the guardianship role in the public area, increase the risk of an offender being found or captured, have a deterrent effect on potential rational offenders, and inhibit the offender's choice to commit crimes in the surveillance cameras area (Clarke, 1997; Jeffery, 1971). While the cameras may not help apprehend the robber on the spot, the recording can be used to identify the robber afterwards. Therefore, cameras can have a deterring effect on street robbery. Cornish and Clarke (2003) regarded the surveillance camera as a formal control, which increases offenders' perceived risk, and thus inhibits robbery. Additional empirical studies in Western content have shown that surveillance cameras can reduce crime, but their effect is minimal (Farrington et al., 2007; Lim & Wilcox, 2017; Ratcliffe et al., 2009). For example, Farrington's research in the UK found that surveillance cameras have a weak deterring effect on overall crime, but it was effective in reducing crimes in train station car parks (Farrington et al., 2007). Ratcliffe's evaluation of Pennsylvania in the United States suggests that while there appears to be a general benefit, there were as many sites that showed no benefit of camera presence as there were locations with a positive outcome on crime (Ratcliffe et al., 2009). Subsequently, the research results of Lim and Wilcox (2017) in Cincinnati, Ohio provided minimal evidence of the effectiveness of surveillance cameras in reducing crime, though some types of crime were reduced in residential areas especially, and effectiveness was clearly interdependent with an area's base rate of crime.

Recently, a non-Western content study also showed that surveillance cameras have a significant deterring effect on crime. For example, a case study from Gusu District in Suzhou, China, Liu et al. (2019) found that surveillance cameras have a significant crime reduction effect, and in terms of crime types, the surveillance cameras have equal reduction effects on the general criminal and public-order cases, and the effect of surveillance cameras on the general theft crime is stronger than those on the specific theft of electric bicycle and the specific theft of battery of electric cars. But these effects decay in time.

In sum, existing research has revealed the various effects of surveillance cameras on curbing crime. However, most of these findings are not directly related to the crime location choice of offenders.

2.3. Crime generators and crime attractors

The built environment affects crime patterns in many ways, and some specific built environments where routine activities concentrated in time and space are found to act as major crime generators and crime attractors (Bernasco & Block, 2011; Brantingham & Brantingham, 1995; Kinney et al., 2008). Crime generators are places that are easily accessible to the public, and they may become crime hotspots because the existence of large crowds creates opportunities for crime (Bernasco & Block, 2011). Typical examples are shopping malls, high schools, transportation hubs, etc. On the other hand, crime attractors are some places that provide certain opportunities, and they don't necessarily converge large crowds at the same time but are featured with frequent cash transactions, making it an ideal "hunting ground" for street robbers. These places include but are not limited to bars, clubs, cybercafés, grocery stores, hotels, restaurants, ATMs, banks and other places (Bernasco et al., 2013; Bernasco et al., 2017; Bernasco & Block, 2011; Haberman & Ratcliffe, 2015; Kurland et al., 2014). For example, Jean (2008) found that robbers in Chicago were mainly attracted to small markets dominated by cash transactions. Consequently, these activity nodes are well suited for motivated street robbers to search for attractive or weakly guarded targets.

Routine activity theory suggests that for a crime to occur in a certain location, a motivated offender must encounter a suitable and unguarded target or victim (Cohen & Felson, 1979). The occurrence of crime is affected by routine activities of the individuals. Their activity nodes play a critical role in the criminal process. Any change in crime opportunities of these nodes affects the occurrence of criminal activities. For example, Brantingham and Brantingham (1995) suggested that these places where people travel to and from routinely, such as work, shopping, leisure, and entertainment; therefore, they have the potential for becoming crime hotspots. A large body of research has studied the relationship between criminal opportunities and environmental factors including specific features of social environment, micro-scale features of built environment, and crime prevention & control (Bernasco et al., 2013; Bernasco et al., 2017; Clancey, 2015; Hanaoka, 2016; He et al., 2020; Long et al., 2020; Long, Liu, Zhou, et al., 2017; Reid & Andresen, 2014; Song et al., 2019; Wilcox et al., 2003).

Crime pattern theory helps explain where offenders commit their crimes (Bernasco et al., 2017; Brantingham & Brantingham, 1993). It holds that crime is most likely to occur in areas where the space of activity coincides between a potential offender and a potential victim (Brantingham & Brantingham, 1981). More specifically, it posits that two conditions are necessary for a crime to happen at a certain location: the place must provide an opportunity for crime, and the potential offender must be aware of this place and its opportunity (Bernasco et al., 2017). Thus, where criminal opportunities and spatial awareness overlap, crime may happen. Because awareness spaces of offenders are maintained and developed in their routine activities, offenders would commit crimes in or near the places where they frequently visit.

The premises of the two aforementioned theories are closely connected. For example, both focus on the change of criminal opportunities. Also, both put a particular emphasis on the interaction between offenders, victims, or targets and guardians, and on the interaction between people and the environment, which are of great importance to the occurrence of crime (Feng et al., 2019).

2.4. Accessibility and proximity

According to routine activity theory, accessibility such as the density of road network reflects the convenience of a neighborhood (or an area) to communicate with the outside world (Xiao et al., 2018). Some studies have shown that the level of accessibility of a neighborhood and the connectedness of a neighborhood to other neighborhoods influence where offenders choose to commit their crimes. For example, Law et al. (2016) found that road density is negatively associated with juvenile crimes in the Regional Municipality of York, Ontario, Canada. Long, Liu, Zhou, et al. (2017) also demonstrated its significant negative impact on outdoor theft in ZG City, China. Further, the distance of journey to crime is used to represent proximity between an offender's home location and crime location (Bernasco et al., 2017). Of all factors that affect crime location choices, distance is by far the most influential (Song et al., 2019). A large number of studies have confirmed that offender's crime location choice is negatively affected by the distance of journey to crime (Baudains et al., 2013; Bernasco et al., 2013; Bernasco et al., 2017; Bernasco & Block, 2009; Johnson & Summers, 2015; Lammers et al., 2015; Long et al., 2018; Menting et al., 2020; Song et al., 2019).

2.5. Social disorganization

Social disorganization theory is often used to explain crimes caused by the change of social environment, and it focuses on how the neighborhood's social composition may inhibit or promote criminal behaviors (Bursik, 1988; Shaw & McKay, 1942). Many studies have shown that central to such theories is the concept of social cohesion, which prompts residents to act collectively to interfere with and prevent crime (Hirschfield & Bowers, 1997; Johnson & Summers, 2015; Sampson et al., 1997). Existing research suggests that social cohesion is more likely to appear in the neighborhoods with stable populations, where residents can form good social ties (Braga & Clarke, 2014; Coleman, 1988; Weisburd et al., 2014), and that residents of a homogeneous neighborhood are more likely to share similar goals and beliefs (Galster & Santiago, 2017; Johnson & Summers, 2015).

Social disorganization theory explains the occurrence mechanism of crimes from three aspects. First, the close social ties between neighbors can form collective efficacy to reduce opportunities for crimes (Weisburd et al., 2014). For example, residents may assert informal control over others who live nearby, reducing the likelihood of their involvement in crimes (Johnson & Summers, 2015). Second, communities with strong socioeconomic heterogeneity or a high proportion of migrant populations are less likely to collectively resist criminal activities because of a lack of cohesiveness among residents who come from very different socioeconomic backgrounds (Hirschfield & Bowers, 1997; Johnson & Summers, 2015). For example, Liu, Jiang, et al. (2017) found that urban villages and old towns in ZG City, China, are the main "hunting grounds" for offenders because of greater human mobility and higher socioeconomic heterogeneity of residents in these areas. Besides, some studies verified that the proportion of youngsters has a significant impact on crime (Browning et al., 2010; Long, Liu, Feng, et al., 2017). Third, the perception of social cohesion by offenders may influence where they decide to commit an offense (Johnson & Summers, 2015). For instance, Bernasco and Nieuwbeerta (2005) consider that social cohesion may act as an impedance factor that deters offenders from targeting a neighborhood.

In sum, crime generators and attractors, accessibility, and social cohesion are usually different types of activity facilities or neighborhood relations, which can significantly affect people's routine activities and social interactions. Ambient population can play the role of either guardian or target. Surveillance cameras may deter crime. There is no research that has integrated these factors in studying offender location choice for street robbery.

3. Research questions and conceptual framework

To fill the aforementioned gap, this study examines the impacts of ambient population and surveillance cameras on street robbery, accounting for the covariates such as crime generators and attractors, accessibility and proximity, and social disorganization. Three research questions and a conceptual framework are put forward.

The first research question is: Does ambient population have a guardianship role in street robbers' crime location choice? So far, existing studies have used data generated by mobile phones to measure the impact of ambient population on crime prediction, but rarely conduct studies to examine its impact on offenders' crime location choice. For example, Bogomolov et al. (2014) found that the combination of mobile phone data and demographic information could be used to predict crime hotspots in London. Hanaoka (2016) estimated the influences of ambient population on snatch-and-run offenses using the temporal change of mobile phone users' locations and found that the effects differ between daytime and nighttime in Osaka City, Japan. Song et al. (2019) found that daily mobility flow generated from mobile phones could help explain thieves' target location choices in ZG City, China. In this article, we will examine whether the ambient population generated by mobile phones is a useful addition to the built and social environment for understanding street robbers' crime location choice, and whether it plays a guardianship role on the street robbers.

The second research question is: Do surveillance cameras play a guardianship role in curbing street robbers' crime location choice? Surveillance cameras are a kind of crime detractor and it acts as a guardianship role (formal control). In particular, some places are formally controlled by surveillance cameras, or security guards, which can deter potential offenders and thus inhibit criminal activities (Kinney et al., 2008). The greater guardianship role in a place, the higher arrest risk for the robbers. For example, Cornish and Clarke (2003) argued that the use of formal control can increase the perceived risk of perpetrators, thereby suppressing the occurrence of street robberies.

The third research question is: Does the integration of ambient population and surveillance cameras increase the explanatory power of the location choice model for street robbery?

Based on the aforementioned theories and literature, a new conceptual framework is designed to illustrate the influence of guardianship role of ambient population and surveillance cameras on street robbers' crime location choice (Fig. 1). This paper hypothesizes that ambient population and surveillance cameras have a guardianship role in street robbers' crime location choice. In other words, the former is the deterrent effect of informal control, while the latter is the inhibition effect of formal control. In addition, crime generators and crime attractors, accessibility and proximity, and social disorganization factors are included in the form of control variables.

4. Data and methods

4.1. Study area and data sets

ZG City is located in the northern part of the Pearl River Delta, on the southeastern coast of China. It is one of the largest cities in China, with a total permanent resident population of 14.90 million in 2018. The GDP was ¥ 2.30 trillion (nearly $ 0.38 trillion) in 2018, with an annual increase rate of 6.50%. The study area covers 1971 communities (Fig. 2), with an average size of 1.62 km^2. The standard deviation of the size of communities is 2.85, the minimum size of 0.001 km^2, and the maximum size of 43 km^2. The data sets used in this paper include crime data and neighborhood characteristics data of ZG City.

4.1.1. Crime data and dependent variables

Crime data on arrested street robbers and their offenses between 2012 and 2016 were provided by the ZG Municipal Public Security Bureau. Following the common practice in crime location choice studies (Bernasco et al., 2015; Bernasco et al., 2017; Lammers et al., 2015; Long et al., 2020; Townsley et al., 2016), this analysis is also limited to the arrested offenders because the addresses of arrested offenders are not available. The importance of the distance of journey to crime in crime location choice has been confirmed by many studies (Baudains et al., 2013; Bernasco et al., 2013; Bernasco et al., 2017; Bernasco & Block, 2009; Johnson & Summers, 2015; Lammers et al., 2015; Long et al., 2018; Menting et al., 2020). This study includes distance as a key control variable.

The dataset included the following information of each arrested robber: the unique offender identifier, the Hukou status, the home address, and the location and time of the robbery. Among a total of 11,455 arrest records in ZG City during 2012–2016, only 7860 records have a home address in the city, involving 7124 robbers. A number of robberies involved multiple robbers. Following the practice of Bernasco et al. (2017), one robber is randomly selected to represent the decision-making of a robbery that involves multiple robbers. This selection leaves 4358 street robbers in the analysis (Table 1).

The data matrix of dependent variables is constructed by using these cases. The calculation of dependent variables in discrete spatial choice modeling refers to the method by Bernasco et al. (2013) and Johnson and Summers (2015). This paper assumes that a street robber chose one for robbery among 1971 communities (1971 alternative sets). The selected neighborhood is recorded as "1"; otherwise, the non-selected one is recorded as "0". Therefore, for each case, it has 1971 rows of data with a "1" and 1970 "0". The "crossing" coding is used in Stata software to construct 8,589,618 (4358*1971) rows of data matrix for estimation.

4.1.2. Neighborhood data, independent variables, and control variables

Neighborhood data include POI data, census data, mobile phone data, and police data. Given the interactive relationship between urban

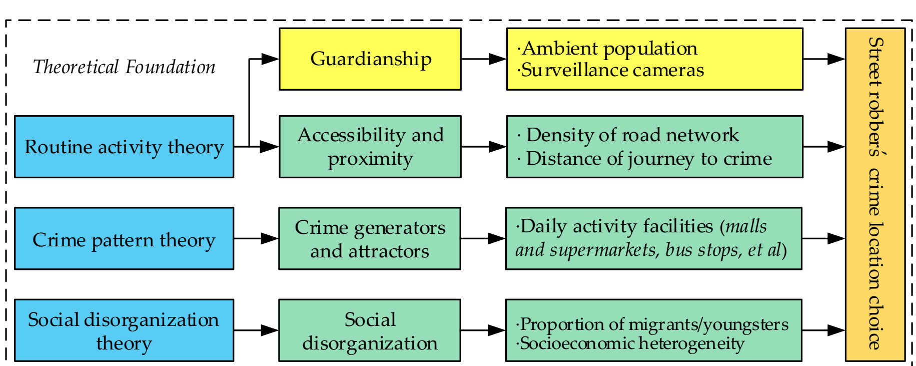

Fig. 1. Conceptual framework on street robbers' crime location choice.

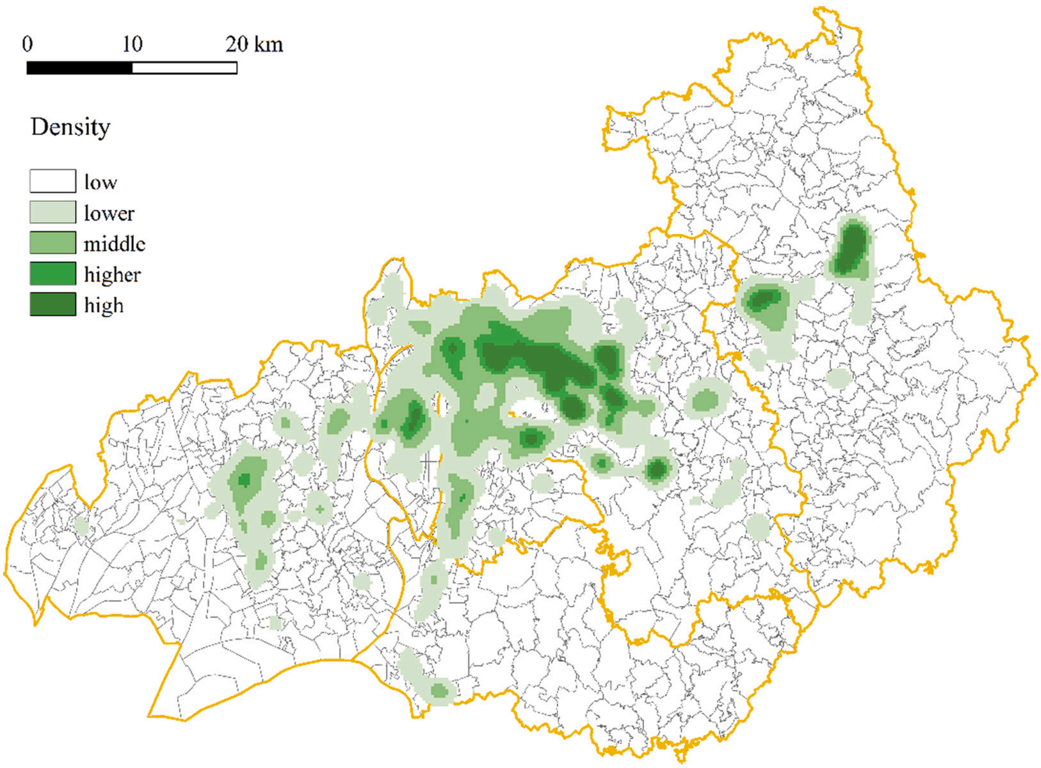

Fig. 2. The kernel density of street robbery in ZG City, China.

Table 1
The basic situation of street robbery cases based on the arrest data. ($N = 4358$).

Number of people involved cases	Arrested records	Number of cases	Cases proportion
1	2646	2646	60.72%
2	1758	879	20.17%
3	1209	403	9.25%
4	812	203	4.66%
5	565	113	2.59%
≥6	870	114	2.62%
Total	7860	4358	100%

crime and environmental factors, one of the shortcomings in previous studies is that most of them do not take into account the impact of ambient population and surveillance cameras. This paper, however, based on controlling for environmental factors includes aspects of built environment and social environment, also considers the influences of ambient population and surveillance cameras on street robbers' crime location choice.

Ambient population is measured by average daily mobility from ZG City's mobile phone signaling data. This data source is desensitized and aggregated mobile phone data obtained from one of China's largest telecommunication operator. Based on the latitudes and longitudes of 52,026 cell towers, we have created Thiessen polygons to represent the service areas of cells. For each cell tower, an evaluated number of mobile phone users, whose devices communicate with it, is measured on an hourly basis during the period of 12–18 May 2016.

Surveillance cameras are derived from ZG City's POI data and measured by their number in a neighborhood. These cameras are mainly installed along main roads, at large gathering places and important facilities. In Chinese cities, surveillance cameras can be divided into two main types according to their ownership. The first type of surveillance cameras is owned by the government. They are mainly installed along main roads, outside of neighborhood main entrances and exits, or important public areas. The second type of surveillance cameras is privately owned, and they are mainly set up inside enterprises, institutions, and communities. This research uses the first-type of surveillance cameras. In line with the research on security equipment and crime (Liebst et al., 2019; Long et al., 2018; Philpot et al., 2020; Reid & Andresen, 2014), surveillance cameras are assumed to play a guardianship role in this study.

The crime attractors and generators are selected based on the literature. Malls and supermarkets, grocers, and terminal markets are selected as retail business facilities (Long, Liu, Feng, et al., 2017; Wang et al., 2017). Bars and clubs, cybercafés, and sports stadiums are aggregated as leisure sports facilities (Bernasco et al., 2017; Bernasco & Block, 2011; Lammers et al., 2015; Roncek & Maier, 1991). High schools, ATMs and banks, and car parks are deemed as public supporting facilities (Baudains et al., 2013; Groff & Lockwood, 2014; Long et al., 2018). Bus stops, transportation hubs, and subway stations are treated as public transport stations (Barnum et al., 2017; Bernasco et al., 2015; Hart & Miethe, 2014; Liu, Zhang, et al., 2017; Summers & Caballero, 2017).

The density of road network is used to represent traffic accessibility (Law et al., 2016; Long, Liu, Zhou, et al., 2017; Xiao et al., 2018), and it is measured by the ratio of the total length of road network in a neighborhood to the area of the same neighborhood.

The distance of journey to crime is the Euclidean distance between the offender's residence and the centroid of each of the 1, 971 neighborhood units. The mean distance is 14.35 km with a standard deviation of 8.89 km. A logarithmic transformation is applied the distance variable, due to its Poisson-like distribution.

Social disorganization is represented by proportion of migrants, proportion of youngsters and socioeconomic heterogeneity are selected as control variables (Bernasco et al., 2017; Bernasco & Block, 2009; Johnson & Summers, 2015; Liu et al., 2018; Long, Liu, Zhou, et al., 2017; Rountree et al., 1994). Similar to previous studies (Li, 2012), we adopt the difference of housing type to measure the heterogeneity of socioeconomic. According to China's census data, the types of housing for neighborhood residents can be divided into five categories: rented houses, self-purchased houses, self-built houses, unit dormitories and others. In Chinese society, the different housing types of residents not only reflect their economic strength and affluence, but also represent different socio-economic groups. Using the index of qualitative variation (Wilcox, 1973), socioeconomic heterogeneity is calculated as follows:

$$SE_i = \left(1 - \sum\nolimits_{k=1}^{n} p_{ki}^2\right) \times 100 \quad (1)$$

Where n is the total number of different socioeconomic groups residing in the neighborhood i, and p_{ki} is the proportion of individuals that belong to socioeconomic group k in the neighborhood i. A larger SE_i value indicates more heterogeneity. In this study, the data for calculating the index is derived from the sixth census of China. To be consistent with previous studies (Bernasco et al., 2015; Johnson & Summers, 2015), this index is divided by 10.

Table 2 provides descriptive statistics of all the variables in this research. Multiple collinearity test of independent and control variables is carried out by correlation and regression analysis (Table 3). The correlations between all pairs of variables range from low to moderate, with the highest value being 0.57. Further, the average VIF is 1.63, with a maximum VIF of 2.49, which is far below the generally accepted value of 4. Therefore, collinearity is not a concern in this study.

4.2. Discrete spatial choice modeling

The discrete spatial choice approach is widely used in microeconomics to analyze discrete choice behavior (Bernasco & Nieuwbeerta, 2005). Based on the theory of random utility, this model assumes that a chooser who faces a set of alternatives must make a choice. Moreover, the chooser evaluates the relative utility associated with each alternative (Townsley et al., 2015). Since offenders' crime location choice is similar to the above choice, Bernasco and Nieuwbeerta (2005) introduced the discrete spatial choice model into the field of criminology and examined the crime location choice of burglars in The Hague, the Netherlands.

Subsequently, some studies have used this model to analyze various crime types. For example, Clare et al. (2009) examined the crime location choices of residential burglars in Perth, Australia; Baudains et al. (2013) investigated the crime location choices of rioters in London, UK; Bernasco et al. (2017) recently explored the time difference of street

Table 2
Descriptive statistics of control variables and independent variables.

Variables	Code	Mean	SD	Min	Max
Control variables					
Malls and supermarkets (#)	X_1	3.264	5.466	0	59
Grocers (#)	X_2	2.277	3.144	0	31
Terminal markets (#)	X_3	1.525	2.559	0	24
Bars and clubs (#)	X_4	1.365	2.338	0	21
Cybercafés (#)	X_5	0.433	0.937	0	11
Sports stadiums (#)	X_6	0.941	2.399	0	47
High schools (#)	X_7	0.460	0.955	0	7
ATMs and banks (#)	X_8	3.919	5.546	0	71
Carparks (#)	X_9	5.813	7.516	0	69
Bus stops (#)	X_{10}	2.911	4.413	0	96
Transportation hubs (#)	X_{11}	0.055	0.370	0	4
Subway stations (#)	X_{12}	0.310	1.196	0	14
Density of road network (km/km^2)	X_{13}	10.824	7.855	1.014	54.068
Proportion of migrants (%)	X_{14}	0.472	0.246	0	1.000
Proportion of youngsters (%)	X_{15}	0.264	0.111	0	0.901
Socioeconomic heterogeneity (10%)	X_{16}	4.740	2.400	0	8.524
Log distance	X_{17}	2.434	0.753	−5.900	4.266
Independent variables					
Ambient population (/10,000)	X_{18}	1.143	2.200	0	26.361
Surveillance cameras (#)	X_{19}	5.495	13.408	0	364

Table 3
Correlation coefficient matrix between independent and control variables.

Code	VIF	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}	X_{13}	X_{14}	X_{15}	X_{16}	X_{17}	X_{18}	X_{19}
X_1	1.97	1																		
X_2	2.36	0.53	1																	
X_3	1.43	0.42	0.44	1																
X_4	1.91	0.36	0.57	0.29	1															
X_5	1.58	0.48	0.50	0.38	0.38	1														
X_6	1.57	0.18	0.26	0.12	0.35	0.17	1													
X_7	1.09	0.16	0.18	0.14	0.13	0.13	0.13	1												
X_8	2.25	0.40	0.55	0.37	0.55	0.32	0.34	0.16	1											
X_9	2.49	0.22	0.53	0.31	0.57	0.22	0.47	0.14	0.56	1										
X_{10}	1.51	0.43	0.28	0.24	0.20	0.21	0.20	0.18	0.31	0.25	1									
X_{11}	1.11	0.11	0.18	0.18	0.10	0.15	0.03	0.03	0.14	0.15	0.10	1								
X_{12}	1.22	0.10	0.24	0.09	0.19	0.04	0.23	0.02	0.31	0.30	0.09	0.22	1							
X_{13}	2.12	−0.26	−0.14	−0.13	−0.08	−0.09	−0.09	−0.11	−0.11	−0.07	−0.40	−0.07	−0.04	1						
X_{14}	1.49	0.35	0.33	0.26	0.17	0.30	0.09	0.13	0.18	0.16	0.17	0.05	0.00	−0.07	1					
X_{15}	1.69	0.40	0.26	0.17	0.14	0.29	0.28	0.09	0.20	0.12	0.34	0.05	0.03	−0.27	0.47	1				
X_{16}	1.42	−0.05	0.07	0.04	0.11	0.06	0.10	0.11	0.08	0.16	−0.08	0.03	0.04	0.45	0.10	−0.14	1			
X_{17}	1.11	−0.01	−0.07	−0.05	−0.08	−0.01	−0.04	−0.02	−0.07	−0.12	0.10	0.02	−0.06	−0.24	−0.08	0.03	−0.21	1		
X_{18}	1.53	−0.16	−0.11	−0.10	−0.10	−0.07	−0.06	−0.07	−0.13	−0.13	−0.23	−0.04	−0.05	0.57	0.02	−0.15	0.25	−0.12	1	
X_{19}	1.21	0.14	0.11	0.12	0.14	0.12	0.36	0.07	0.12	0.20	0.17	0.00	−0.08	−0.09	0.11	−0.21	−0.09	−0.04	−0.06	1

Note: the independent and control variables have been standardized in the collinearity testing and the discrete spatial choice modeling.

robbers' location choices in Chicago, USA. In all cases, researchers discussed how offenders' crime location choices were affected by a series of factors, including but not limited to, criminogenic places, human activity.

After controlling for prior offenses at the neighborhood level, this paper assumes that a street robber will choose a neighborhood with the maximized utility to commit a subsequent crime. The utility function is calculated as follows:

$$U_{ij} = \beta x_{ij} + \varepsilon_{ij} \tag{2}$$

where U_{ij} is the expected utility of a robbery in neighborhood j for street robber i, x_{ij} are the values of the explanatory variables for neighborhood j for street robber i, β is a vector of coefficients to be estimated, and ε_{ij} is the random error component of the model.

The utility function can be estimated by a conditional logit model (McFadden, 1978). The probability of street robber i choosing neighborhood j can be calculated as follows:

$$\mathrm{Prob}(Y_i = j) = \frac{e^{\beta x_{ij}}}{\sum_i e^{\beta x_{ij}}} \tag{3}$$

where Y_i is the choice made by street robber i. All models are estimated using STATA 13.0. Besides, it is necessary to explain the overall fitting accuracy of the model. In addition, it should be pointed out that considering the overall fitness of the model, the Pseudo R^2 for discrete spatial choice models is always much lower than those for ordinary least squares regression models. It had been confirmed that if Pseudo R^2 is greater than 0.20, models can be considered as excellent fitness to the data (McFadden, 1978).

5. Results

The results of discrete spatial choice models (Odds Ratios, *Z*-scores, Pseudo R^2, significance level with 95% confidence intervals) are listed in Table 4. Among the four models, Model 1 is a basic model, Model 2 and Model 3 are combined models, and Model 4 is a full model. In Model 1, only the variables of crime generators and crime attractors, accessibility, and social disorganization (built and social environment) are considered. Then, based on Model 1, the variables of daily human mobility (representing ambient population) and surveillance cameras are incorporated into Model 2 and Model 3, respectively. Finally, the variables of above four dimensions are simultaneously integrated into Model 4.

In Table 4, the odds ratios of variables smaller than 1 indicate negative effects, and the smaller the odds ratios are, the greater the negative effects are. On the contrary, the odds ratios of variables larger than 1 indicate positive effects, and the larger the odds ratios are, the greater the positive effects are. For example, in Model 4, the odds ratio of the density of road network is 0.589, which means the density of road network in a neighborhood increases by 1 unit, the odds that a street robber targets the same neighborhood decrease by 41.1%. Similarly, the odds ratio of subway stations is 1.050, which means the number of subway stations in a neighborhood increases by 1 unit, the odds that a street robber targets the same neighborhood increase by 5%. Moreover, if the significance level (*P*-value) of the variable is closer to 0, the variable will be more statistically significant. Besides, the explanatory power of each model is measured by Pseudo R^2, and the larger the Pseudo R^2 is, the higher the explanatory power of the model is.

It should be pointed out that the odds ratios of most of variables in this paper aren't much greater than 1 or far less than 1, which is consistent with the literature that examined the location choice of a large number of offenders (Bernasco et al., 2017; Johnson & Summers, 2015; Lammers, 2018; Song et al., 2019). A closely related study by Song et al. (2019) modeled the location choice of 3436 offenders for theft in the ZG city, and the odds ratios of most variables were close to 1 as well.

The results of Model 1 show that grocers, ATMs and banks, Carparks, and socioeconomic heterogeneity do not have significant effects, while malls and supermarkets, and bus stops have the largest effects. With one more mall and supermarket or bus stop in the neighborhood unit, the odds of being chosen increase by 17.6% and 9.7% respectively. In terms of effect size, the other facilities including terminal markets, bars and clubs, cybercafés, sports stadiums, high school transportation hubs, and subway stations are less influential, which could be related to their smaller quantities. Meantime, a one-unit increase in the proportion of migrants in the neighborhood units increases the odds of the unit being targeted by 9.0%. Accessibility has a very strong and negative impact on the offender's target choice: the higher the density of the road network, the less likely a neighborhood unit is to be chosen as the crime site. In particular, the logged distance of journey to crime has a very strong and negative effect on the offender's crime location choice: the closer to the offender's residence, the more likely a neighborhood unit is to be chosen as a crime site.

This paper first discusses the effects of ambient population. Results of Model 2 verifies the first research question that ambient population has a guardianship role in street robbers' crime location choice. The pseudo

Table 4
Results of the discrete spatial choice modeling.

Variables	Model 1		Model 2		Model 3		Model 4	
	OR	Z	OR	Z	OR	Z	OR	Z
Malls and supermarkets	1.176***	15.36	1.176***	15.36	1.177***	15.39	1.177***	15.39
Grocers	1.018	1.14	1.018	1.14	1.018	1.08	1.018	1.09
Terminal markets	1.056***	4.23	1.056***	4.23	1.057***	4.30	1.057***	4.30
Bars and clubs	1.068***	4.25	1.068***	4.25	1.068***	4.22	1.068***	4.22
Cybercafés	1.083***	6.47	1.083***	6.47	1.084***	6.50	1.084***	6.49
Sports stadiums	0.970*	−2.06	0.970*	−2.06	0.974	−1.70	0.974	−1.69
High schools	1.083***	6.19	1.083***	6.19	1.083***	6.25	1.083***	6.25
ATMs and banks	1.003	0.17	1.003	0.17	0.999	−0.04	0.999	−0.05
Carparks	0.992	−0.41	0.992	−0.41	0.995	−0.25	0.995	−0.26
Bus stops	1.097***	8.93	1.097***	8.93	1.097***	9.03	1.098***	9.03
Transportation hubs	1.049***	6.22	1.049***	6.22	1.049***	6.16	1.049***	6.16
Subway stations	1.052***	4.43	1.052***	4.42	1.050***	4.31	1.050***	4.30
Density of road network	0.590***	−17.72	0.592***	−15.13	0.587***	−17.80	0.589***	−15.21
Proportion of migrants	1.090***	4.07	1.091***	4.07	1.089***	4.03	1.090***	4.03
Proportion of youngsters	1.034	1.81	1.034	1.81	1.038*	2.00	1.038*	2.00
Socioeconomic heterogeneity	1.011	0.53	1.011	0.53	1.014	0.70	1.014	0.70
Log distance	0.313***	−139.54	0.313***	−139.54	0.313***	−139.51	0.313***	−139.51
Ambient population	–	–	0.915***	−6.27	–	–	0.915***	−6.28
Surveillance cameras	–	–	–	–	0.961*	−2.35	0.961*	−2.43
Pseudo R^2	0.264		0.285		0.283		0.289	

Note: $^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$; OR = Odds Ratios (one-tailed).

R^2 value is 0.285 indicating the second model has a better explanatory ability, meanwhile, the odds ratio of variable daily human mobility is 0.915, and its *P* value was less than 0.001, which means the influence of ambient population is negative and highly statistically significant. That is to say, ambient population generated by mobile phones plays a guardianship role in street robbers' crime location choice.

Model 3 confirms the second research question that surveillance cameras play a guardianship role in curbing street robbers' crime location choice. The pseudo R^2 value is 0.283, meanwhile, the effect of the variable surveillance cameras in 95% of confidence level is statistically significant, and with an estimated odds ratio of 0.961. Consequently, this finding demonstrates that surveillance cameras have a negative impact on street robbers' crime location choice. That is to say, surveillance cameras also play a guardianship role in street robbers' criminal activities. Interestingly, we find that the guardianship effect of surveillance cameras is smaller than that of ambient population, and the reasons for the above will be explained in the discussion section.

In line with the third research question, the Pseudo R^2 of 0.289 of Model 4 is the highest, roughly a 10% increase over the 0.264 of Model 1 but marginal improvements over Models 2 and 3 (Table 4). The explanatory power of these models is explained as follows. Firstly, by comparing Pseudo R^2 between Model 1 and Model 2, it can be concluded that the explanatory power of Model 2 has been improved by 7.20%. In other words, the findings of this article demonstrate that adding the ambient population generated by mobile phones to estimate the impact of environment factors on street robbers' crime location choice is effective. Secondly, compared with model 1, the explanatory power of model 3 has been improved by 7.95%. Therefore, the findings of this article also confirm the effectiveness of adding surveillance cameras to assess the influence of environment factors on the choice of crime location for street robbers. Finally, it is particularly noteworthy that Model 4's explanatory power has been improved by roughly 10%. Compared with the first model, the fourth model considers the impacts of guardianship role and environment factors on street robbers' crime location choice, so it's more comprehensive and has the highest explanatory power.

6. Discussion

In the current study, we conclude that ambient population plays a guardianship role and has a negative and deterrent impact on street robbers' crime location choice. That is, the greater ambient population is, the less likely the street robbers are to commit crimes in the neighborhood. Consequently, our finding is consistent with those of Boivin on that the relationship between crime location choices in burglary and ambient populations was negative (Boivin, 2018). However, this finding is different from the opinion of Song et al. that ambient population has a significantly positive effect on thieves' target location choices (Song et al., 2019). However, such discrepancy is not really surprising, due to reasons below.

First, the impact of ambient population, like many other factors, may vary by crime type. As we all know, disaggregated crime types have different spatial and temporal patterns (Ackerman & Rossmo, 2015; Andresen et al., 2016), and the geographic extent of environmental factors (e.g. facility's criminogenic) influence various types of crime (Groff & Lockwood, 2014). Besides, routine activity theory holds that an increased human presence in a given area is expected to be associated with both an increase and a decrease in criminal activity (Boivin, 2018). Similarly, the role of ambient population changes with different crime types. For example, in the case of theft from the person (TFP), there is a positive relationship between ambient population and criminal opportunities. In a realistic urban society, the more daily human mobility in a place, the more chaotic or crowded scenes can be created, which provides a good criminal opportunity for TFP, and thus more conducive for thieves' crime location choices. But for street robbery, there is a negative relationship between ambient population and criminal opportunities. Felson and Eckert (2015) believed that ambient population may also act as guardians by their simple presence. Consequently, the increase in ambient population can form more potential informal control, and street robbers are more likely to be caught. According to rational choice theory (Clarke & Felson, 1993; Felson & Clarke, 1998), if the arrest risk in a place is higher, the less likely offender commits a crime in that place. Because of the high crime risk, therefore, the rational street robbers would not choose to commit crimes in a place with a large ambient population. In other words, street robbery does not require as many potential victims as TFP. The more population around street robbers, the more it inhibits their crime.

Street robbers usually follow single pedestrians, especially women and elderly people. They unexpectedly rob victims and then quickly escape the crime scene. They may also ambush the victim, such as hiding in a secluded corner and waiting for a suitable target to appear. It should be noted that daily human mobility in the neighborhood indicates the street activities of residents to a certain extent. For instance, in densely populated areas with many street activities, which is not conducive to street robbers committing crimes and fleeing, because ambient population is more likely to detect and suppress their violent crimes. That is to say, an increase in street activities can play a role in the natural monitoring of streets, allowing residents in leisure to pay attention to strangers and abnormal behaviors, especially to juveniles and youngsters, which forms an effective informal social control to inhibit criminal behavior.

In short, rational street robbers understand when they carry out robberies, the guardianship of ambient population is likely to deter them from committing an illegal behavior, or they are likely to be caught by ambient population. For example, in ZG City's arrest record, a considerable number of street robbers were captured on the spots by the citizens (Long et al., 2018). This evidence also supports the guardianship role of the ambient population.

Second, the timeliness of discovery varies by TFP and street robbery. TFP has a high degree of concealment and may not be detected by the victims right away. For example, TFP occurs at a moment of slight contact, and the victim may not know his wallet was stolen until a later time. If a place has a larger ambient population, TFP can have more targets. Conversely, street robberies are instantly felt by the victim at the time of the attack. Once a victim is robbed, the offender is immediately exposed. A large ambient population can help apprehend the robbers.

Our research adds to the literature (He et al., 2020; Song et al., 2019) that ambient population generated from mobile phones could help explain offenders' crime location choice. We expect to see more research taking advantage of the increasing availability of automatically collected geo-referenced measures of human presence through mobile phones, location-enabled APPs, GPS tracking, and social media such as Tweets.

In terms of surveillance cameras, we find they also play a guardianship role and have significant negative impacts on street robbers' crime location choice. The more the surveillance cameras in a neighborhood are, the greater the deterrent effect on street robbers is. Consequently, our finding is similar to most Western or non-Western context research results (Farrington et al., 2007; Lim & Wilcox, 2017; Liu et al., 2019; Ratcliffe et al., 2009), namely, surveillance cameras have a deterrent effect on offender's crime location choice.

Besides, our finding is consistent with previous studies on security equipment with a focus on small places or groups of people in small places (Groff et al., 2015; Kinney et al., 2008; Kubrin et al., 2010; Long et al., 2018; Reid & Andresen, 2014; Sampson & Cohen, 1988). These studies adopt strategies to solve problems through careful analysis of local conditions, which seem to be effective at reducing crime. Surveillance cameras, as a type of formal control (Cornish & Clarke, 2003), increase the perceived risk of offenders, thus inhibiting the occurrence of street robbery.

There are other types of formal controls. For example, police patrol is a major formal control in most cities. However, patrol related information is highly confidential in China. Therefore, this article focused on surveillance cameras to represent the formal guardianship in the neighborhood.

Additionally, we find that the explanatory power is the highest after the basic model is integrated with ambient population and surveillance cameras. That is to say, it provides the strongest explanations for street robbers' crime location choice, and presents a type of method that can more realistically depict the relationship between guardianship role (or environment factors) and street robbers' crime location choice. In modern cities, street robbers are not only influenced by crime generators and attractors, accessibility and proximity, and social disorganization, but influenced by the guardianship role of ambient population and surveillance cameras. Because of this, we should also take into account the intervention of human activities and prevention and control measures while analyzing the environmental effect on offenders' crime location choices. Only in this way can it help us better understand where street robbers choose to commit crimes.

Finally, we find it interesting that the guardianship role of surveillance cameras is less than that of ambient population. To further support and verify the findings of the discrete spatial choice method, we use negative binomial regression and partial least square regression to replicate the study. Both models confirm that the guardianship role of ambient population outweighs that of surveillance camera. Consequently, we believe the difference in their guardianship role is objective.

7. Conclusions

This paper is strongly rooted in the large body of literature on routine activity theory, crime pattern theory, and social disorganization theory. Most previous studies focused on the impacts of built environment and social environment, without regard to the impact of guardianship role of ambient population and surveillance cameras on street robbers' crime location choice.

This study demonstrates that ambient population and surveillance cameras have a negative impact on street robbers' crime location choice, and they play a guardianship role in street robbers' criminal activities. In particular, we find that the guardianship effect of ambient population is greater than that of surveillance cameras. Previous research on offenders' crime location choice has often explored the relationship between the resident population and where crimes occur. However, our findings provide insights on how the ambient population helps explain the location choice of street robbers. The targets of the robbers are not necessarily local residents, people from other neighborhoods can be targeted as well. Further, we verify that the explanatory power is the highest after the basic model is integrated with ambient population and surveillance cameras, which can more realistically depict the influence of guardianship role and environmental factors on street robbers' crime location choice, and to a certain extent, improve our understanding on their interaction.

Rapid urban expansion and economic development attract people to large cities in China. The widening gap between the rich and the poor is becoming increasingly apparent, leading to complex social problems. Surveillance cameras are prevalent, to maintain social order. The findings of this study may provide scientific insight to the city government on urban planning and deployment of surveillance cameras for crime prevention. To take advantage of the guardianship role of ambient population, mixed land use that attracts pedestrian traffic should be encouraged in urban planning and urban renewal. Also, considering the guardianship role of surveillance cameras, the optimization of the camera placement may help maximize their effects.

Statement

The following are our statements for the submitting of our paper entitled "Ambient population and surveillance cameras: the guardianship role in street robbers' crime location choice" to *Cities*:

(1). the manuscript is our original research;
(2). It has not been submitted elsewhere in print or electronic form to another journal or as a proposed book chapter;
(3). It has not been published previously or otherwise accessible to the public (e.g., posted on website);
(4). No similar or exact submission will be sent elsewhere until your review is completed.
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Declaration of competing interest

None.

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References

Ackerman, J. M., & Rossmo, D. K. (2015). How far to travel? A multilevel analysis of the residence-to-crime distance. *Journal of Quantitative Criminology, 31*(2), 237–262.
Ackerman, W. V., & Murray, A. T. (2004). Assessing spatial patterns of crime in Lima, Ohio. *Cities, 21*(5), 423–437.
Andresen, M. A. (2011). The ambient population and crime analysis. *The Professional Geographer, 63*(2), 193–212.
Andresen, M. A., Curman, A. S., & Linning, S. J. (2016). The trajectories of crime at places: Understanding the patterns of disaggregated crime types. *Journal of Quantitative Criminology, 33*(3), 427–449.
Andresen, M. A., & Jenion, G. W. (2010). Ambient populations and the calculation of crime rates and risk. *Security Journal, 23*(2), 114–133.
Angel, C. M., Sherman, L. W., Strang, H., Ariel, B., Bennett, S., Inkpen, N., et al. (2014). Short-term effects of restorative justice conferences on post-traumatic stress symptoms among robbery and burglary victims: A randomized controlled trial. *Journal of Experimental Criminology, 10*(3), 291–307.
Barnum, J. D., Caplan, J. M., Kennedy, L. W., & Piza, E. L. (2017). The crime kaleidoscope: A cross-jurisdictional analysis of place features and crime in three urban environments. *Applied Geography, 79*(1), 203–211.
Baudains, P., Braithwaite, A., & Johnson, S. D. (2013). Target choice during extreme events: A discrete spatial choice model of the 2011 London riots. *Criminology, 51*(2), 251–285.
Bernasco, W., & Block, R. (2009). Where offenders choose to attack: A discrete choice model of robberies in Chicago. *Criminology, 47*(1), 93–130.
Bernasco, W., & Block, R. (2011). Robberies in Chicago: A block-level analysis of the influence of crime generators, crime attractors, and offender anchor points. *Journal of Research in Crime and Delinquency, 48*(1), 33–57.
Bernasco, W., Block, R., & Ruiter, S. (2013). Go where the money is: Modeling street robbers' location choices. *Journal of Economic Geography, 13*(1), 119–143.
Bernasco, W., Johnson, S. D., & Ruiter, S. (2015). Learning where to offend: Effects of past on future burglary locations. *Applied Geography, 60*(4), 120–129.
Bernasco, W., & Nieuwbeerta, P. (2005). How do residential burglars select target areas? A new approach to the analysis of criminal location choice. *British Journal of Criminology, 45*(3), 296–315.
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. *Journal of Research in Crime and Delinquency, 54*(2), 244–275.
Bogomolov, A., Lepri, B., Staiano, J., Oliver, N., Pianesi, F., & Pentland, A. S. (2014). Once upon a crime: Towards crime prediction from demographics and Mobile data. In *Proceedings of the 16th international conference on multimodal interaction* (pp. 427–434). Istanbul, Turkey: ACM.
Boivin, R. (2018). Routine activity, population(s) and crime: Spatial heterogeneity and conflicting propositions about the neighborhood crime-population link. *Applied Geography, 95*(6), 79–87.
Braga, A. A., & Clarke, R. V. (2014). Explaining high-risk concentrations of crime in the city: Social disorganization, crime opportunities, and important next steps. *Journal of Research in Crime and Delinquency, 51*(4), 480–498.
Brantingham, P. J., & Brantingham, P. L. (1981). *Environmental criminology*. Beverly Hills, CA: Sage Publications.
Brantingham, P. L., & Brantingham, P. J. (1995). Criminality of place: Crime generators and crime attractors. *European Journal on Criminal Policy and Research, 3*(3), 5–26.

Brantingham, P. L., & Brantingham, P. L. (1993). Nodes, paths, and edge considerations on the complexity of crime and the physical environment. *Journal of Environmental Psychology, 13*(1), 3–28.

Browning, C. R., Byron, R. A., Calder, C. A., Krivo, L. J., Kwan, M. P., Lee, J. Y., et al. (2010). Commercial density, residential concentration, and crime: Land use patterns and violence in neighborhood context. *Journal of Research in Crime and Delinquency, 47*(3), 329–357.

Bursik, R. J. (1988). Social disorganization and theories of crime delinquency: Problems and prospects. *Criminology, 26*(4), 519–552.

Clancey, G. (2015). Think crime! Using evidence, theory and crime prevention through environmental design (CPTED) for planning safer cities. *Crime Prevention and Community Safety, 17*(1), 67–69.

Clare, J., Fernandez, J., & Morgan, F. (2009). Formal evaluation of the impact of barriers and connectors on residential Burglars' macro-level offending location choices. *Australian and New Zealand Journal of Criminology, 42*(2), 389–416.

Clarke, R. V., & Felson, M. (1993). *Routine activity and rational choice: Advances in criminological theory (Vol. 5)*. New Brunswick, USA: Transaction Publisher.

Clarke, R. V. G. (1997). *Situational crime prevention*. Monsey, N Y: Criminal Justice Press.

Cohen, L. E., Cantor, D., & Kluege, J. R. (1981). Robbery victimization in the United States: An analysis of a nonrandom event. *Social Science Quarterly, 62*(4), 644–657.

Cohen, L. E., & Felson, M. (1979). Social change and crime rate trends: A routine activity approach. *American Sociological Review, 44*(4), 588–608.

Coleman, J. S. (1988). Social capital in the creation of human capital. *American Journal of Sociology, 94*(Suppl. 1), 95–121.

Conklin, J. E. (1972). *Robbery and the criminal justice system*. Philadelphia: Lippincott.

Cook, P. J. (2009). Robbery. In M. Tonry (Ed.), *The Oxford handbook of crime and public policy*. Oxford: Oxford University Press.

Cook, P. J., & Ludwig, J. (2000). *Gun violence: The real costs*. New York: Oxford University Press.

Cornish, D. B., & Clarke, R. V. (2003). Opportunities, precipitators and criminal decisions: A reply to Wortley`s critique of situational crime prevention. *Crime Prevention Studies, 16*, 41–96.

Farrington, D., Gill, M., & Waples, S. (2007). The effects of closed-circuit television on crime: Meta-analysis of an English national quasi-experimental multi-site evaluation. *Journal of Experimental Criminology, 3*(1), 21–38.

Felson, M., & Clarke, R. V. (1998). Opportunity makes the thief: Practical theory for crime prevention. *Police Research, 1*(1), 1–36.

Felson, M., & Eckert, M. (2015). *Crime and everyday life* (5th ed.). Thousand oaks: Sage.

Feng, J., Liu, L., Long, D., & Liao, W. (2019). An examination of spatial differences between migrant and native offenders in committing violent crimes in a large Chinese City. *ISPRS International Journal of Geo-Information, 8*(3), 1–19.

Gale, J., & Coupe, T. (2005). The behavioural, emotional and psychological effects of street robbery on victims. *International Review of Victimology, 12*(1), 1–22.

Galster, G., & Santiago, A. (2017). Neighbourhood ethnic composition and outcomes for low-income Latino and African American children. *Urban Studies, 54*(2), 482–500.

Gialopsos, B. M., & Carter, J. W. (2015). Offender searches and crime events. *Journal of Contemporary Criminal Justice, 31*(1), 53–70.

Groff, E. R., & Lockwood, B. (2014). Criminogenic facilities and crime across street segments in Philadelphia: Uncovering evidence about the spatial extent of facility influence. *Journal of Research in Crime and Delinquency, 51*(3), 277–314.

Groff, E. R., Ratcliffe, J. H., Haberman, C. P., Sorg, E. T., Joyce, N. M., & Taylor, R. B. (2015). Does what police do at hot spots matter? The Philadelphia policing tactics experiment. *Criminology, 53*(1), 23–53.

Haberman, C. P., & Ratcliffe, J. H. (2015). Testing for temporally differentiated relationships among potentially criminogenic places and census block street robbery counts. *Criminology, 53*(3), 457–483.

Hanaoka, K. (2016). New insights on relationships between street crimes and ambient population: Use of hourly population data estimated from mobile phone users locations. Environment and Planning. B, Planning & Design, 0(0), 1–17.

Hart, T. C., & Miethe, T. D. (2014). Street robbery and public bus stops: A case study of activity nodes and situational risk. *Security Journal, 27*(2), 180–193.

He, L., Páez, A., Jiao, J., An, P., Lu, C., Mao, W., et al. (2020). Ambient population and larceny-theft: A spatial analysis using mobile phone data. *ISPRS International Journal of Geo-Information, 9*(6), 342.

He, L., Páez, A., & Liu, D. (2017). Built environment and violent crime: An environmental audit approach using Google Street View. *Computers, Environment and Urban Systems, 66*, 83–95.

Hipp, J. R., Bates, C., Lichman, M., & Smyth, P. (2019). Using social media to measure temporal ambient population: Does it help explain local crime rates? *Justice Quarterly, 36*(4), 718–748.

Hirschfield, A., & Bowers, K. J. (1997). The effect of social cohesion on levels of recorded crime in disadvantaged areas. *Urban Studies, 34*(8), 1275–1295.

Jean, P. K. B. S. (2008). *Pockets of crime: Broken windows, collective efficacy, and the criminal point of view*. Chicago, USA: The University of Chicago Press.

Jeffery, C. R. (1971). *Crime prevention through environmental design*. Beverly Hills, CA: Sage Publications.

Johnson, S. D., & Summers, L. (2015). Testing ecological theories of offender spatial decision making using a discrete choice model. *Crime & Delinquency, 61*(3), 454–480.

Kinney, J. B., Brantingham, P. L., Wuschke, K., Kirk, M. G., & Brantingham, P. J. (2008). Crime attractors, generators and detractors: Land use and urban crime opportunities. *Built Environment, 34*(1), 62–74.

Kubrin, C. E., Messner, S. F., Deane, G., McGeever, K., & Stucky, T. D. (2010). Proactive policing and robbery rates across US cities. *Criminology, 48*(1), 57–97.

Kurland, J., Johnson, S. D., & Tilley, N. (2014). Offenses around stadiums: A natural experiment on crime attraction and generation. *Journal of Research in Crime and Delinquency, 51*(1), 5–28.

Kwan, M. (2016). Algorithmic geographies: Big data, algorithmic uncertainty, and the production of geographic knowledge. *Annals of the American Association of Geographers, 106*(2), 274–282.

Lammers, M. (2018). Co-offenders' crime location choice: Do co-offending groups commit crimes in their shared awareness space? *The British Journal of Criminology, 58*(5), 1193–1211.

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.

Law, J., Quick, M., & Chan, P. (2016). Open area and road density as land use indicators of young offender residential locations at the small-area level: A case study in Ontario, Canada. *Urban Studies, 53*(8), 1710–1726.

Levy, M. P. (2009). *Opportunity, environmental characteristics, and crime: An analysis of auto theft patterns*. El Paso, TX: LFB Scholarly Publishing, LLC.

Li, Z. (2012). Housing conditions, patterns and mechanisms of second generation migrants in urban China: A case study of six large cities. *Acta Geographica Sinica, 67*(2), 189–200.

Liebst, L., Philpot, R., Bernasco, W., Dausel, K., Ejbye-Ernst, P., Nicolaisen, M., et al. (2019). Social relations and presence of others predict bystander intervention: Evidence from violent incidents captured on CCTV. *Aggressive Behavior, 45*, 598–609.

Lim, H., & Wilcox, P. (2017). Crime-reduction effects of open-street CCTV: Conditionality considerations. *Justice Quarterly, 34*(4), 597–626.

Liu, L., Feng, J., Ren, F., & Xiao, L. (2018). Examining the relationship between neighborhood environment and residential locations of juvenile and adult migrant burglars in China. *Cities, 82*, 10–18.

Liu, L., Jiang, C., & Li, L. (2019). The effects of police CCTV camera on crime: A case study from Gusu District in Suzhou, China. *Scientia Geographica Sinica, 39*(1), 61–69.

Liu, L., Jiang, C., Zhou, S., Liu, K., & Du, F. (2017). Impact of public bus system on spatial burglary patterns in a Chinese urban context. *Applied Geography, 89*(12), 142–149.

Liu, L., Zhang, C., Feng, J., Xiao, L., He, Z., & Zhou, S. (2017). The spatial-temporal distribution and influencing factors of fraud crime in ZG city, China. *Acta Geographica Sinica, 72*(2), 315–328.

Long, D., Liu, L., Chen, J., Xiao, L., Song, G., & Xu, C. (2020). Impact of prior crime experiences of street robbers on subsequent crime location choices. *Progress in Geography, 39*(5), 815–828.

Long, D., Liu, L., Feng, J., Song, G., He, Z., & Cao, J. (2017). Comparisons of the community environment effects on burglary and outdoor-theft: A case study of ZH peninsula in ZG city. *Aata Geographica Sinica, 72*(2), 341–355.

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. *Sustainability, 10*(6), 1–16.

Long, D., Liu, L., Zhou, S., Du, F., Song, G., & Xiao, L. (2017). Research progress of criminal behavior from the perspective of geography. *Progress in Geography, 36*(7), 886–902.

Malleson, N., & Andresen, M. A. (2015). Spatio-temporal crime hotspots and the ambient population. *Crime Science, 4*(1), 1–8.

Mburu, L. W., & Helbich, M. (2016). Crime risk estimation with a commuter-harmonized ambient population. *Annals of the American Association of Geographers, 106*(4), 804–818.

McFadden, D. (1978). Quantitative methods for analysing travel behaviour of individuals: Some recent developments. In D. A. Henser, & P. R. Stopher (Eds.), *Behavioural travel modelling* (pp. 279–318). London, England: Croom Helm.

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. *The British Journal of Criminology, 60*(2), 303–322.

Newman, O. (1996). *Creating defensible space*. Washington, DC: US Department of Housing and Urban Development Office of Policy Development and Research.

Panigutti, C., Tizzoni, M., Bajardi, P., Smoreda, Z., & Colizza, V. (2017). Assessing the use of mobile phone data to describe recurrent mobility patterns in spatial epidemic models. *Royal Society Open Science, 4*(5), 1–13.

Philpot, R., Liebst, L., Lindegaard, M. R., Bernasco, W., & Levine, M. (2020). Would I be helped? Cross-national CCTV footage shows that intervention is the norm in public conflicts. *The American Psychologist, 75*(1), 66–75.

Ratcliffe, J. H., Taniguchi, T., & Taylor, R. B. (2009). The crime reduction effects of public CCTV cameras: A multi-method spatial approach. *Justice Quarterly, 26*(4), 746–770.

Reid, A. A., & Andresen, M. A. (2014). An evaluation of CCTV in a car park using police and insurance data. *Security Journal, 27*(1), 55–79.

Roncek, D. W., & Maier, P. A. (1991). Bars, blocks, and crimes revisited: Linking the theory of routine activities to the empiricism of "hot spots". *Criminology, 29*(4), 725–753.

Rountree, P. W., Land, K. C., & Miethe, T. D. (1994). Macro-micro integration in the study of victimization: A hierarchical logistic model analysis across Seattle neighborhoods. *Criminology, 32*(3), 387–414.

Sampson, R. J., & Cohen, J. (1988). Deterrent effects of the police on crime: A replication and theoretical extension. *Law and Society Review, 22*(1), 163–190.

Sampson, R. J., Raudenbush, S. W., & Earls, F. J. (1997). Neighborhoods and violent crime: A multilevel study of collective efficacy. *Science, 277*(5328), 918–924.

Shaw, C. R., & McKay, H. D. (1942). *Juvenile delinquency and urban areas*. Chicago: University of Chicago Press.

Silberman, C. E. (1978). *Criminal Violence, Criminal Justice*. New York: Random House.

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. *Journal of Quantitative Criminology, 35*, 831–854.

Song, G., Liu, L., Bernasco, W., Xiao, L., Zhou, S., & Liao, W. (2018). Testing indicators of risk populations for theft from the person across space and time: The significance of mobility and outdoor activity. *Annals of the American Association of Geographers, 108*(5), 1370–1388.

Summers, L., & Caballero, M. (2017). Spatial conjunctive analysis of (crime) case configurations: Using Monte Carlo methods for significance testing. *Applied Geography, 84*(7), 55–63.

Townsley, M., Birks, D., Bernasco, W., Ruiter, S., Johnson, S. D., White, G., et al. (2015). Burglar target selection: A cross-national comparison. *Journal of Research in Crime and Delinquency, 52*(1), 3–31.

Townsley, M., Birks, D., Ruiter, S., Bernasco, W., & White, G. (2016). Target selection models with preference variation between offenders. *Journal of Quantitative Criminology, 32*(2), 283–304.

Vespignani, A. (2009). Predicting the behavior of techno-social systems. *Science, 325*(5939), 425–428.

Wang, F., Hu, Y., Wang, S., & Li, X. (2017). Local Indicator of colocation quotient with a statistical significance test: Examining spatial association of crime and facilities. *The Professional Geographer, 69*(1), 22–31.

Weisburd, D., Groff, E. R., & Yang, S. (2014). Understanding and controlling hot spots of crime: The importance of formal and informal social controls. *Prevention Science, 15*(1), 31–43.

Wilcox, A. R. (1973). Indices of qualitative variation and political measurement. *The Western Political Quarterly, 26*(2), 325–343.

Wilcox, P., Quisenberry, N., & Jones, S. (2003). The built environment and community crime risk interpretation. *Journal of Research in Crime and Delinquency, 40*(3), 322–345.

Xiao, L., Liu, L., Song, G., Ruiter, S., & Zhou, S. (2018). Journey-to-crime distances of residential burglars in China disentangled: Origin and destination effects. *ISPRS International Journal of Geo-Information, 7*(8), 1–15.