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Theft from the person in urban China: assessing the diurnal effects of opportunity and social ecology

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A R T I C L E I N F O

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A B S T R A C T :

Opportunity theories and ecological theories are commonly used to explain spatial crime patterns, but diurnal variations in these patterns have received little attention. Furthermore, the theories have been developed in Western countries, and it has remained unclear whether they are also applicable in China, and how their core concepts can be measured in the Chinese context. We use official crime data from a large Chinese city to investigate whether neighborhood rates of theft from the person are related to characteristics of the population (ecological perspective) and to the presence of transport and retail facilities that shape daily activities (opportunity perspective). We test whether effects of these characteristics differ between daytime and nighttime. Our findings demonstrate that both theories are applicable to crime analysis in China, and that temporal variations should not be ignored. Furthermore, care is required regarding the operationalization of the concepts.

1. Introduction

Decades of research have shown that variations in crime across urban neighborhoods are ubiquitous (Glaeser, Sacerdote, & Scheinkman, 1996; Shaw & McKay, 1942). These variations have been explained by two dominant theoretical frameworks, opportunity theories and social ecological theories. Although both perspectives strongly rely on the whereabouts and behavior of people (Pratt & Cullen, 2005), the diurnal mobility of populations is ignored in most of the present literature. It is implicitly assumed that populations are static, although in most urban environments populations are highly mobile, and continuously change locations over the course of the day to engage in different activities (Haberman & Ratcliffe, 2015).

Another implicit assumption in the extant literature is that opportunity theories and social ecology theories apply equally across different continents and cultures. However, both frameworks have been developed in North-America, West-Europe and Australia, but their usefulness is seldom tested elsewhere. China presents an ideal testbed for the evaluation of these two frameworks. Housing 18.5 percent of the world population, China has undergone a very fast process of urbanization over the last forty years, with rapid economic development and substantial changes in urban structures and major social developments. There has been a growing concern about the increase of social issues, such as social stratification, urban poverty, migrant concentration and crime (Yuan & Wu, 2014). Still, it has remained an open question whether opportunity theories and social ecology theories explain the spatial distribution of crime in a culture that differs in so many ways from the United States and other Western countries.

The aim of this study is twofold. The first aim is to investigate whether the explanatory power of both perspectives can be improved by considering diurnal variation. We incorporate the mobility of the population by distinguishing daytime and nighttime theft rates, respectively. Mobility varies strongly between daytime and night time. Daytime activities involve going to work and pursuing other outdoor activities that may take place outside their own neighborhood. At night most people return home.

The second aim of this study is to assess whether the key concepts of these two approaches can be fruitfully applied in China. It has yet to be demonstrated that these concepts can be correctly measured in the Chinese context by using the same types of variables as are used in the Western industrialized world. For example, racial heterogeneity is a major element of social disorganization in most Western countries, whereas in China, there is no obvious racial heterogeneity. Instead, the difficulties that rural migrant workers face in integrating with local

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populations, facilitates social disorganization. Some elements of routine activity patterns are also different. Alcohol consumption in public establishments like bars, for example, is a common and popular entertainment activity in most Western countries, but not in China. With respect to land use, commercial facilities, like restaurants and convenience stores, are typically dispersed in China, while in Western countries, they tend to be more spatially concentrated. Therefore, in this study we carefully consider not only the effects of social and infrastructural elements on crime, but also the proper measurement of these elements in the Chinese context.

Our analysis focuses on thefts from the person. Like the authorities in other countries, local governments in China highly prioritize city safety. As property crimes are much more common than violent crimes, thefts from the person (TFP) are a major public safety issue in China and a core topic in urban crime prevention initiatives. TFP refers to situations in which offenders covertly steal properties from the victims in public or semi-public places, for example by pick-pocketing or by taking away valuables while the owners are distracted.

2. Literature review

2.1. Theoretical framework

The opportunity framework includes routine activity, crime pattern and rational choice theories, and it emphasizes geographic variations in criminal opportunities (Brantingham & Brantingham, 1984; Carroll & Weaver, 1986; Sampson & Wooldredge, 1987). Routine activity theory asserts that motivated offenders, suitable targets and absence of guardians are the three necessary conditions for crime (Cohen & Felson, 1979). Where potential and suitable victims' routine activities overlap in time and space with those of motivated offenders, crime is a possible result. Crime pattern theory is fully comparable with routine activity theory, but it adds to routine activity theory a more detailed description of offenders' and victims' activity spaces (Brantingham, Brantingham, & Andresen, 2017) and the notion that locations can function as crime generators and crime attractors (Kinney, Brantingham, Wuschke, Kirk, & Brantingham, 2008). In general, crime is related to land use or criminogenic places and it is hypothesized that the busier a place is, the larger the number of potential targets and thus criminal opportunities for motivated offenders there will be (Bernasco & Block, 2011; Copes, 1999; McCord, Ratcliffe, Garcia, & Taylor, 2007; Steenbeek, Völker, Flap, & van Oort, 2012). Rational choice theory is a generic theory of behavior that stresses the goal-directed and optimizing nature of human decision-making, including criminal decision-making (Cohen, 1981). It assumes, for example, that thieves prefer maximal profits and minimal effort and risk of apprehension.

Since the works of the Chicago School, the social ecological framework has been influential in the study of geographic variations in crime (Bursik, 1988; Pratt & Cullen, 2005; Taylor, 1997). Ecological theories "seek to explain variations in crime rates through the differing incentives, pressures, and deterrents that individuals face in different environments" (Kelly, 2000, p. 530). The most important ecological theory is social disorganization theory, in which the social characteristics of the neighborhood and its residents are related to lack of social organization and social control (Boessen & Hipp, 2015; Seddon, 2006; Shaw & McKay, 1942). The composition of a community, in terms of the characteristics of its residents, is tightly related to social control as well as to social disorganization (Osgood & Anderson, 2004). Jacobs (1961) observed that informal social control, also known as "eyes on the streets", is crucial to restrain disorder and crime. However, informal social control is voluntary behavior and it requires collective efficacy, i.e. mutual trust and cohesion amongst residents (Sampson, Raudenbush, & Earls, 1997). It has been found that poverty, ethnic heterogeneity, and residential mobility lower collective efficacy and thereby facilitate deviant behavior and crime (Osgood, Wilson, Omalley, Bachman, & Johnston, 1996; Rice & Smith, 2002).

In our analysis of urban crime rates in China we will apply both the opportunity framework and the ecological framework, as their combination has proven to be necessary and useful in many Western countries. Smith, Frazee, and Davison (2000) proposed to integrate the theories of social disorganization and routine activity for the analysis of street robbery in a medium-sized U.S. city. Using the integrated theoretical framework, Rice and Smith (2002) carried out empirical research to study the diffusion of automobile theft, and found that the integration of the two approaches increased the predictive power of their models.

2.2. Temporal concern

People's behavior is strongly constrained both temporally and spatially, and the effect of time should be taken into account (Haberman & Ratcliffe, 2015; Ratcliffe, 2006). The temporal rhythms of residents (and formal guardians like police officers) have an influence on the offending opportunities of potential offenders (Ackerman & Rossmo, 2015; Bernasco, 2010; Bernasco, Johnson, & Ruiter, 2015). As a result, opportunities for crime are not homogeneous across space and time and the function of social ecology may also change (Martin, Cockings, & Leung, 2015). Quantitatively speaking, the impact of potentially criminogenic places on crime is thought to be a function of time, as some of the model parameters are not temporally stable (Ceccato & Uittenbogaard, 2014; Haberman & Ratcliffe, 2015; He, Paez, Liu, & Jiang, 2015). For example, studying street robbery in Philadelphia, Haberman and Ratcliffe (2015) distinguished four different periods of the day and found that some effects varied across the different periods. Bernasco, Ruiter, and Block (2016), however, demonstrated that location choices of street robbers in Chicago hardly varied across twelve 2-h time blocks of the day, the effects of high school presence being the only exception.

However, except the literature mentioned above, time effects, especially the diurnal variation, are neglected in most studies of the urban geography of crime, both in the Western world and in China.

2.3. Crime research on China

There has been some empirical work applying both opportunity and social ecology approaches to crime in China (Chen et al., 2017; Liu & Li, 2017). Feng, Dong, and Song (2015) described the spatial and temporal changes of crime patterns for weeks in different years. Consistent with the opportunity theory literature, commercial land use is supposed to generate a concentration of people who form the potential targets for offenders. Liu, Song, and Xiu (2016) demonstrated that violent crime in Changchun City is strongly concentrated in the central city area and that this concentration can be explained by characteristics of the neighborhood's socioeconomic and demographic attributes, and in particular by land use.

However, besides the temporal effects of some risk factors, the contemporary literature about crime in China does not address the criminogenic effects of specific facilities, and does not distinguish between stores, bars, restaurants, transit stations, or other types of facilities.

In terms of social ecology, factors like poverty and residential stability have been demonstrated to affect crime rates in China. Jiang, Wang, and Lambert (2010) found that residential stability increased informal social control in Guangzhou. Zhang, Messner, and Liu (2007) used a multilevel model to study the risk of household burglary in Tianjin. They demonstrated the applicability of Western criminological theory to China but also noted some important differences.

Characteristics of the social ecology in China are much more complicated than what has usually been measured in social research. With a large number of migrants from rural areas and increasing attraction to the highly-educated, Chinese cities tend to have very heterogeneous population. Individuals cannot easily be classified on the basis of a single attribute, such as education or age. Instead, because education may be correlated with housing, occupation, income or other variables, it is important to conduct a multivariate analysis of the social ecology, and find a better way to carve the profile of the population. Because the effects of the social ecology on crime are far less examined in China as compared to the Western world, it is necessary to tease out which specific indicators of opportunity and social ecology theories are applicable in the Chinese context when analyzing the spatial distribution of urban crimes.

3. Data and method

Data from the urban area of a large Chinese city (ZG city [1]) are used to investigate whether neighborhood rates of theft from the person are related to characteristics of the population (ecological perspective) and to the presence of transport and retail facilities that shape daily activities (opportunity perspective). ZG city is in the southeast of China and has a population larger than 10 million. Its developed economy has attracted many people from other places in China.

To account for temporal variability in daily activities, we distinguish two broad temporal categories, namely daytime (7:00–19:00) and nighttime (19:00–7:00), a distinction that also approximately coincides with the sunlight-darkness distinction and the typical points of time at which most people go out for activities and get back home.

3.1. Unit of analysis

Police station service areas (Pai Chu Suo, PCS) are adopted here as the basic study units. The police station is the grass-root agency of the Chinese police organization. It has jurisdiction over several census units. The service area of a PCS is smaller in the city center and larger in the outskirts, because the population density in the center is much larger than in the outskirts. The whole study area is 3518 km^2, with a mean value of PCS is roughly 20 km^2 (first quartile 2.53 km^2, median 7.92 km^2, third quartile 20.93 km^2). Although there is no gold standard for a particular neighborhood unit, police station service areas are larger than the spatial units in most other research on neighborhoods. Some authors are advocating a micro spatial unit of analysis, such as street blocks or street segments, in order to minimize heterogeneity within units (Bernasco & Block, 2011). Nevertheless, the police station service area is still a good choice for two reasons.

First, micro units are too small to measure the broad effects of crime indicators as well as the social environment. For example, a larger unit can better capture the racial heterogeneity of an area than a street block (Hipp, 2007; Krivo & Peterson, 1996). Boessen and Hipp (2015) found that many neighborhood factors seem to have a much broader impact rather than only operate on the micro scale. Townsley et al. (2015) carried out a cross national comparison on burglar target selection based on a meso level. The units they chose for Brisbane, Australia were neighborhoods with a mean area of 8.48 km^2, a minimum value of 0.7 km^2 and maximum value of 184.85 km^2.

Second, police stations are the root agencies of security, and have a very active interaction with local communities. As Zhong (2009) succinctly pointed out, "policing in China is by its nature in the community, for the community, and by the community." Zhang, Messner, and Zhang (2017) found that local police officers not only shoulder the responsibility of residents' security but also help solve a wide range of problems, such as mediating disputes in neighborhoods. Moreover, due to the overlap of police services, residents within specific police station service areas share the common experience of social control, which is also one important dimension to help shape neighborhoods (Bellair, 1997). In an empirical study, Liu et al. (2016) used 74 police precincts as the basic units for spatial statistical analysis of Changchun's violent crimes and found that neighborhood socioeconomic, demographic, especially land use characteristics are effective in accounting for the spatial variation in the distribution of violent crimes across the city of Changchun.

Based on thses considerations, police station service areas have the advantage of capturing a broader effect of the social and physical environment, as well as the social control exercised by the local police.

3.2. Crime data

The crime data, from January 2014 to December 2014, are aggregated data with hourly time stamp of theft from the person from the Public Security Bureau of ZG city. The TFP rate in each police station service area is calculated for the two periods respectively, dividing the numbers of TFP incidents by the residential population (TFP per 10,000 residents). A total of 177 police station service areas are used in the analysis. Because police station services record only cases of TFP that take place within their service area, all TFPs reported by a police station service can be assigned to that service area. As the police station service area is the spatial unit of analysis, no further geocoding was necessary.

3.3. Opportunity data

Opportunity variables include subway stations, bus stops, restaurants, entertainment facilities, department stores, bars, convenience stores and net bars (also known as cybercafé or Internet café, seldom appear in the Western literature). All of them are obtained with exact geographical coordinates from a map and navigation company. In China, the Internet is widely used but not available to everyone and net bars are important places for the accessibility to Internet (Hong & Huang, 2005). Computer usage of young people is closely supervised by parents and teachers, therefore some adolescents visit net bars to access the Internet, play computer games and socialize with peers in the absence of adult supervision (Li, Zhang, Lu, Zhang, & Wang, 2014; Liang, Zhou, Yuan, Shao, & Bian, 2016).

With the exception of subway stations, all variables are measured as densities. Densities are calculated by dividing the number of the specific facilities by the residential population (per 10,000). The entertainment facilities comprise karaoke bars, night clubs, pubs, and cinemas. The department stores mainly refer to toggeries where people go shopping besides their daily supplies.

Compared to the other variables, subway stations are sparsely distributed, and the number of subway stations per police station service areas varies little. Most are below 2. Therefore, in this study, the presence of subway stations is coded as a dummy variable to indicate whether there is at least one subway station in the specific police station service area.

3.4. Social ecology data

To measure elements of the social ecology, a wide range of indicators from the 2010 census is taken into consideration. These indicators cover many elements of the traditional (Western) framework of social disorganization theory, and include the distributions of different demographic characteristics (resident's age, education level, aging household, marriage status and occupation) and housing situation (home ownership, rent level, housing condition, age and size of the residential unit). Housing conditions include average room number and per capita living space of residents' housing. They also include locally significant characteristics such as *Hukou* status.

The "*Hukou*" regulation, or the household registration system, is an important means for the Chinese government to separate migrants from the countryside from native residents that have been living in the city for a long time. *Hukou* status strongly correlates with the quality of education, housing and medical services. The presence of many migrants without local *Hukou*, leading to segregation, lowered well-being, poverty or other social ills, has become an important issue in the Chinese context (Zhang, Messner, Liu, & Zhuo, 2009).

Many of these social ecological variables are strongly correlated

Table 1
Indicators of the census and loadings of the main factors.

Factor	Indicator	Coefficient	Factor	Indicator	Coefficient
Factor 1	Education: Middle school and below	−0.839	Factor 2	Age: 19-30	−0.765
	Education: High school	0.770		Age: 46-60	0.924
	Education: Under Graduate and above	0.703		Age: Over 60	0.952
	Hukou: Non-agricultural population	0.720		Aging household: Owner with elder over 65	0.943
	Occupation: Institutions responsible	0.600		*Hukou*: Native with local *Hukou*	0.789
	Occupation: Professional & technical	0.880		Marriage status: Above 15 and unmarried	−0.656
	Occupation: Clerks	0.635		Rent level: 1000 and below	0.452
	Occupation: Primary sector	−0.500		House age: Before 1979	0.781
	Occupation: Equipment operators	−0.658		House age: After 2000	−0.750
	Home ownership: Second-hand house owner	0.627		Housing condition: Average room number	0.787
	Home ownership: Owner of the original public-housing	0.605		Housing condition: Per capita living space	0.837
	Rent level: 1000–2000 Yuan	0.716		Size of home:81–120 m^2	0.790
	Rent level: 2001–3000 Yuan	0.626		Size of home: Above 150m^2	0.724
Factor 3	Home ownership:Self-built house	−0.630	Factor 4	Age: 31-45	0.857
	Home ownership: Other kinds of house renter	0.750		Marriage status: Married	0.840
	Size of home: Under 80 m^2	0.976	Factor 6	Rent level: 3001 and above	0.845
Factor 5	*Hukou*: Migrants with local *Hukou*	0.673	Factor 7	Home ownership: Low-rent housing renter	0.620
	Occupation: Sales and service	0.519			
	Home ownership: Commercial housing owner	0.636		Home ownership: Economically affordable housing owner	0.686

NOTE: Factor 1: Well-Educated; Factor 2: Native population; Factor 3: Rural migrant workers; Factor 4: Middle-age; Factor 5: Migrants-settlement; Factor 6: High-income; Factor 7: Affordable housing. The value of coefficients is extracted from the rotated component matrix, equal to the correlation coefficients.

with each other. For example, the higher educated live in larger houses and pay more rent than the lower educated, and *Hukou* status is correlated with age and education. In order to prevent multi-collinearity issues in the regression analysis, a factor analysis was used to reduce the dimensionality of the data and to extract the main underlying factors. Another reason for resorting to factor analysis is that China is culturally and politically different from most Western countries. We did not want to make a priori assumptions based on the Western literature on what the most useful combinations of census indicators are in the context of urban China. In order to engage with the existing Western literature on social disorganization, we also compared the main social disorganization variables with what we identify as the 'social factor' in this study.

A total of 9 categories and 37 indicators from the sixth national population census data are used in this study (Table 1). Two steps are used to process the data. First, for each indicator, its percentage in the total population or in the total number of households is calculated. Then principal component analysis and varimax orthogonal rotation are applied to extract the main factors. The value of the Kaiser-Meyer-Olkin test was 0.717 and the significance of the Bartlett sphericity test was less than 0.001. Both outcomes prove that the result of factor analysis is acceptable. Finally, 7 main factors are extracted and their accumulated variance contribution rate is as high as 79.4%. According to the correlation matrix, if the absolute value of correlation index between an indicator and the main factor is larger than 0.5, the indicator would be regarded as one of the characteristics of the factor. A description and interpretation of the 7 extracted factors are as follow.

3.5. Features of the factors and their interpretation

As is shown in Table 1, age and marriage status mainly load on Factor 2 and Factor 4. Level of education loads high on Factor 1, which also has a stronger relationship with the occupations. Different *Hukou* status refers to different factors (Factor 1, 2 and 5). Home ownership status has a connection with education level and it can also help identify the specific group (like Factor 7). The rent level refers to Factor 1, 2 and 6. House age, housing condition and size of the residential unit can be well loaded on Factor 2. The smallest unit size (under 80 m^2) has a strong correlation with Factor 3. Factors 1 to 7 provide a good description of the categories of the population in the ZG city. Compared to the indicators of a single aspect, the factor analysis gives a better profile of the mass.

3.5.1. Factor 1: well-educated factor

In Table 1, there are 11 indicators positively related to factor 1 and those correlation coefficients higher than 0.7 are indicators of professional & technical, high school, non-agricultural population, 1000–2000 Yuan (rent level) and under graduate and above (education level). It can be concluded that Factor 1 mainly refers to those who are well educated and occupied in a professional and technical career. They can afford the relatively high rent and some of them have bought a second hand or an original public house.

3.5.2. Factor 2: native population factor

Factor 2 shows obvious characteristics of the aging, local *Hukou*, houses built before 1979 and large residential unit. Besides, it is also strongly negatively related to the young population (19–30) and new housing built after 2000. ZG city is a big and developed city that attracts large amounts of young people from less developed areas while natives are relatively old. Factor 2 reflects the features of the native population well.

3.5.3. Factor 3: rural migrant workers factor

Factor 3 is strongly related with those living in small houses (under 80 m^2) and renting houses. This group often live densely in or near the city center, in consistency with the character of rural migrant workers. Meanwhile, it is negatively related with self-built housing which is usually built in the outskirt area by the locals. Therefore, Factor 3 is labeled as the rural migrant workers factor.

3.5.4. Factor 4: middle-age factor

The fourth main factor shows obvious characteristics of people who are middle-aged (31–45) and married. Other indicators have a weak relationship with this factor. As a result, Factor 4 is labeled the middle-age factor.

3.5.5. Factor 5: migrants-settlement factor

Indicators of migrants with local *Hukou*, commercial housing owners and those employed in the sales and service labor markets are principally loaded on Factor 5, which mainly represents commodity house owners who are also migrants but can settle down and change their *Hukou* to the ZG city. They may include residents who came to the city quite early when the housing price was low.

Table 3
Descriptive statistics of the variables.

	Min	Max	Average	S.D
Dependent variable				
Night-time TFP Volume	0.000	1055.000	236.282	198.370
Day-time TFP Volume	2.000	1429.000	487.209	363.623
Night-time TFP Rate	0.000	825.603	42.232	64.102
Day-time TFP Rate	8.291	3181.818	141.725	299.931
Population (10,000)	0.108	17.720	6.175	3.444
Opportunity variables				
Subway Stations (Dummy variables)	0.000	1.000	0.469	0.500
Bus station Density (per 10,000)	0.000	39.422	9.820	7.185
Restaurants Density (per 10,000)	0.000	148.423	21.624	15.527
Entertainment Facilities Density (per 10,000)	0.000	3.091	0.454	0.510
Department stores Density (per 10,000)	0.000	134.519	13.413	17.389
Bar Density (per 10,000)	0.000	3.183	0.366	0.593
Net Bar Density (per 10,000)	0.000	2.911	0.730	0.556
Convenience Stores Density (per 10,000)	0.000	18.988	2.787	2.181
Social ecology variables				
Well-educated factor	−1.502	3.045	−0.007	0.990
Native population factor	−2.332	2.090	0.004	0.996
Rural migrant workers factor	−2.600	1.909	0.005	0.988
Middle-age factor	−6.896	2.099	−0.019	1.000
Migrants-settlement factor	−2.629	2.897	0.033	1.000
High-income factor	−1.987	10.219	−0.001	1.012
Affordable housing factor	−2.378	4.948	−0.010	0.968

3.5.6. Factor 6: high-income factor

Factor 6 mainly shows the characteristics of high housing rent (higher than 3000 Yuan), indicating that this group has better economic and living conditions. The high-rent residential places (F6) are often close to the CBD (Central Business District) where workers earn relatively high incomes and can afford the high rent.

3.5.7. Factor 7: affordable housing factor

Economically affordable housing and low-rent housing typically load on Factor 7. These two kinds of housing are usually subsidized by the government and sold or rented at a lower price than market value. They often locate in the same place. However, it needs to be pointed out that not all low income households can move in, due to limited resources. They need to apply to government and the government would allocate the houses based on the applicants economical and moral conditions.

3.6. Method

Crime rate analyses typically apply either ordinary least squares regression, Poisson regression or negative binomial regression. The OLS model assumes that the dependent variable follows a normal (Gaussian) distribution conditional on the covariates. However, the TFP rate likely violates this assumption. From the distribution of the dependent variable, we know that it is over-dispersed and that negative binominal regression is a better choice in this sense. Osgood (2000) gave a systematic demonstration on how to use the negative binominal regression to deal with crime rate. The basic Poisson regression model is like Equation (1). λ_i is the number of TFP for case i. X is an explanatory variable. β_k is a regression coeeficient, where β_0 is a constant multiplied by 1 for each case.

$$\ln(\lambda_i) = \sum_{k=0}^{K} \beta_k x_{ik} \tag{1}$$

When the model is applied to the crime rate, λ_i is divided by the size of the residential population(n_i), as in equations (2) and (3).

$$\ln\left(\frac{\lambda_i}{n_i}\right) = \sum_{k=0}^{K} \beta_k x_{ik} \tag{2}$$

$$\ln(\lambda_i) = \ln(n_i) + \sum_{k=0}^{K} \beta_k x_{ik} \tag{3}$$

By fixing the coefficient of the residential population to the value of 1, the residential population size is used as an exposure measure, and the negative binominal regression effectively analyzes the per capita TFP instead of the TFP counts (Osgood, 2000). Collinearity tests were carried out to check for and avoid multi-collinearity problems in all independent variables. Variance Inflation Factor (VIF) values are all below 2.44 and correlation coefficients are no larger than 0.5, indicating that multi-collinearity issues are not present.

Like other multivariate regression models, the negative binomial model assumes independence among observations, conditional on the values of the covariates. The conditionality on the covariates is important here, because it implies that independence of observations should be assessed not with respect to the dependent variable, but with respect to the residuals of the model (Kühn & Dormann, 2012). To test independence amongst observations, we calculated Moran's I (Moran, 1950), a common measure of spatial autocorrelation, on the Pearson residuals of the two estimated models. Moran's I estimates of both Model 1 and Model 2 (in Table 4) are not significant, indicating that spatial dependence is not an issue in this study and does not produce bias in the coefficient estimation.

4. Results

First, the descriptive statistics are given to introduce the basic information of the dependent variables and independent variables (Table 3). The rate of TFP in the daytime is obviously larger than that in the night- time. Subsequently, the negative binominal regression model is built for the TFP rate in the daytime and in the night-time respectively. Finally, we use the Wald test to examine the differences of the estimated coefficients between daytime and nighttime.

4.1. Regression models

In Model 1 (Table 4), the presence of subway stations is related to increasing crime risk. If there is a subway station, it would add (1.252–1) * 100% more crimes. Densities of bus stations and restaurants density have positive effects on crime, in which each one-unit increase is expected to increase crime by 4.0% and 1.5% respectively. Besides, the increase of crime can also be a result of the presence of department stores and net bars, as a one-unit increase is associated with an increase in the TFP rate by 1.1% and 24.7% respectively. However, a one-unit increase in the density of the convenience stores, would decrease the TFP rate by 5.3%. The densities of entertainment facilities and bars have no significant impact on theft.

Effects of social factors on the TFP rate in day-time period show that the well-educated factor and the rural migrant workers factor are related to the increasing of the TFP rate, nevertheless the affordable housing factor would lower the TFP rate. An upgrade of 28.6% and 27.9% of crime rate would happen if one unit increased in the well-educated factor and the factor of rural migrant workers respectively. As a contrast, the TFP rate would decrease by 9.7% from a one-unit increase in the affordable housing factor. Factors of the native population, the middle-age, the migrants-settlement and the high-income have no significant impact on TFP.

Model 2 shows the results for the night time period between 19:00–6:59. The presence of the subway stations, restaurants, department stores and net bars increases the risks of theft significantly. The presence of a subway station increases the TFP rate by 31.9%. Comparable figures for bus stations, restaurants, department stores and net bars are 1.5%, 2.3%, 0.7% and 31.9%. But a one-unit increase in the

Table 4
Results of negative binominal regression models and the Wald test of estimated coefficients.

Variables	Model 1 (daytime)		Model 2 (nighttime)		Wald test
	Coef.	IRR	Coef.	IRR	Day-Night
Cons	3.380	29.364	2.562	12.965	–
Residential population (exposure)	1.000		1.000		–
Opportunity variables					
Subway Stations	0.225*	1.252	0.277***	1.319	n.s.
Bus station Density	0.039***	1.040	0.015**	1.015	***
Restaurants Density	0.015***	1.015	0.023***	1.023	***
Entertainment Facilities Density	0.107	1.113	0.116	1.123	n.s.
Department stores Density	0.011**	1.011	0.007**	1.007	n.s.
Bar Density	−0.074	0.929	0.027	1.027	n.s.
Net Bar Density	0.221*	1.247	0.277***	1.319	n.s.
Convenience Stores	−0.054*	0.947	−0.054**	0.948	n.s.
Social ecology variables					
Well-educated factor	0.251***	1.286	0.171***	1.187	**
Native population factor	0.011	1.011	−0.067	0.935	**
Rural migrant workers factor	0.246***	1.279	0.198***	1.219	*
Middle-age factor	0.044	1.045	−0.004	0.996	**
Migrants-settlement factor	0.058	1.060	0.137***	1.147	**
High-income factor	0.058	1.060	0.020	1.020	n.s.
Affordable housing factor	−0.102*	0.903	−0.001	0.999	***
AIC	2403.7		2055.6		–
BIC	2457.7		2109.6		–
Moran's I value of residuals	−0.016		−0.014		–

*p < 0.05, **p < 0.01, ***p < 0.001, n.s. means not significant.

density of the convenience stores decreases the TFP rate by 5.2%. Densities of entertainment facilities and bars are not significant.

As for the social ecology factors, the well-educated, the migrants-settlement factor and the rural migrant workers factor serve to enhance the risk of TFP with the margin effects of 18.7%, 14.7% and 21.9% respectively. The native population, the middle-age, the high-income and the affordable housing group have no significant impact on the TFP rate.

4.2. Diurnal comparison

The Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) are both relative measures of model fit. When the AIC of two models (that need not be nested) are compared, the model with the smaller AIC value fits better with the data than the model with a largest AIC value, and the same holds for the BIC. From the values of AIC and BIC of Model 1 and Model 2, we conclude that the fit of the night-time model is better than that of the daytime model. The TFP rate variation in the night is easier to explain than that in the day.

The Wald test is used to test differences of individual coefficients between the daytime and nighttime models. At the significance level of 0.05, Table 4 shows that only two of the opportunity variables, density of bus stations and of restaurants, have significantly different effects between day and night. The effect of bus station density is stronger in the day than in the night, while the effect of restaurant density is stronger in the night. In terms of the social ecology variables, only the high-income factor presents no difference for the whole day, the others differ between day and night. The well-educated factor and the rural migrant workers factor have stronger positive effects on TFP in the daytime while the migrants-settlement factor has a stronger positive effect in the nighttime.

The factors of native population and middle-age have no significant influence on TFP all the day long despite their significant difference between day and night. Compared to the effects in the night, the affordable housing factor has significantly stronger negative effects on TFP in the day.

5. Discussion and conclusions

Informed by opportunity theories and ecological theories, this study identified relevant factors affecting the rate of TFP in urban neighborhoods in the Chinese context, and tested whether these factors have different effects at daytime and nighttime.

The findings indicate that diurnal differentiation should not be ignored. Indeed, some factors, especially the social factors that describe the neighborhood population, affect neighborhood TFP rates differently at daytime and nighttime. These differences appear to be related to the diurnal patterns of the population, which impact the volume of the ambient population in the neighborhoods, and thereby both the number of targets and the amount of social control exercised. In addition, this study has shown that opportunity theories and the social ecology theories are simultaneously applicable to crime analysis in China like they are in the Western world. Care is required, however, regarding the operationalization of concepts, in particular the social ecological variables. For example, racial heterogeneity hardly informs the measurement of social disorganization in China, whereas elements of the *Hukou* household registration system are strictly needed to capture variations in social disorganization across Chinese neighborhoods. In terms of the time difference, the effect of the bus station density on TFP in the daytime is weaker than that in the night time. This is probably because in the night time, the bus services are reduced and the volume of the passengers turns smaller as well. This situation is opposite to that of restaurants, where most people go to dinner after work at the end of the day.

As for the social ecology factors, the well-educated factor and the rural migrant workers factor have stronger positive effects in the daytime. Unlike the findings in the Western literature (Osgood & Anderson, 2004; Shaw & McKay, 1942), the well-educated factor in this study suggests that the educational background of neighborhood residents is not necessarily related to the amount of social disorganization or social control in the area. Instead, in the Chinese context a well-educated population may be indicative of the presence of suitable targets. This factor is strongly related with occupation, which is probably the reason why it has stronger effects on theft rate in the daytime.

Where the rural migrant workers live, population density is usually high. It features high anonymity and therefore leads to weaker social control and more disorganization. In the day, everyone is busy working and vigilance is reduced. In the nighttime, activities slow down and social control improves, making it more difficult to perpetrate crimes than in the day.

The migrants-settlement factor has a stronger attraction to thieves in the night than in the day. It is probably because they will go back to their commercial house which is often located in gated community, therefore lowering the guardianship on the streets.

Unlike the conclusion that low-income housing would increase crime (Glaeser et al., 1996; McNulty & Holloway, 2000; Roncek, Bell, & Francik, 1981), the affordable housing factor can reduce the TFP in the daytime, though not in the night. The subsidized housing, offered by their employers or the city government, partly linking to work units (Wang & Murie, 2010), seems to reduce the TFP rate.

The native population factor is supposed to indicate the presence of strong social ties, and therefore stronger informal social control, and is thus expected to have a negative effect on the TFP rate, but the results show that it has no obvious impact. The absence of this effect might be attributed to the fast development of China and the increasingly frequent movement of the population within the whole country. Large proportions of the population do not live near where they were raised, and these changes have transformed the traditional Chinese acquaintance society.

Age and marriage status, reflected by middle-age factor, have no significant impact on the TFP rate. The result of the high-income factor indicates that the residents with high income may not be the preferred target choices as they may have little interaction with offenders of TFP.

In line with the predictions of the opportunity approach, the results of most variables derived from the opportunity approach are consistent with findings reported in the literature (Bernasco & Block, 2011; Copes, 1999; Haberman & Ratcliffe, 2015). Subway stations, bus stations, restaurants and department stores are busy places and attract large amounts of suitable victims. As a result, the presence of these facilities heightens the TFP rate. Conversely, the convenience stores variable has a negative coefficient, possibly indicating a social control function for TFP reduction. The estimated effects of entertainment facilities density and of bar density do not significantly affect the TFP rate. Unlike the situation in Western countries (Steenbeek et al., 2012), bars are not a frequent leisure choice for the citizens in ZG city. The business of the net bar is a notable indicator that may help explain the TFP rate in the Chinese context. Net bars seem to function as crime attractors, as they bring together a population of young people with potential deviant attitudes and behaviors.

Many of the estimated effects of the social ecology variables generated by a factor analysis of census data are not in line with those in the extant literature. Nevertheless, the social ecology analysis indicates that the factor analysis method can help define neighborhood categories that cannot be identified by separate isolated indicators. It can reveal the relationship between different types of neighborhood residents and give a rich description of the population. From the analysis, we know that age and marriage status of the neighborhood population do not influence the TFP rate. Their educational background, also related to their occupation, refers to their potential suitability as targets but not to social disorganization. In addition, we find that living space or residential size instead of *Hukou* status better represents the presence of rural migrant workers, which connects to social disorganization. Concentration of people with local *Hukou* does not seem to facilitate crime prevention against TFP. The temporal differentiation can also shed lights on policing: Hot spot policing should have a careful consideration of time, as it can improve the efficiency of limited police strength and resources.

There are some limitations to this study that should be highlighted here. First, ZG city, a super big city with a developed economy and a large floating population, may not be representative of cities with lower degrees of urbanization. Second, only TFP is examined in this study. Future research are needed to address whether the opportunity approach and the social ecology approach can be applied to other crimes in China as well. Third, it is also important to note this study is carried out at meso perspective and the grass-root government unit (PCS) is used as the basic spatial unit of analysis. Due to limitations in the data, comparisons between outcomes at different scales were not feasible.

The results of this study also provide some ideas for future research. The mobility pattern of the population is the fundamental logic underlying the present study: crime follows where people go. In particular, the volume of TFP depends strongly on the size of the ambient (as opposed to resident) population (Andresen, 2011; Malleson & Andresen, 2016). Mobility patterns are very complicated, however, but far from random. In particular, in Chinese cities a strong activity space segmentation exists for populations with different income levels (Zhou, Deng, Kwan, & Yan, 2015). More precise measures of the routine activities of people with different income levels would help explore their relationship with the TFP rate in a greater detail. While the distinction between day and night is proven useful in this study, finer temporal resolution may yield additional insight.

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Note

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.

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