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Do Spatial Spillover Effects of Crime Matter in Urbanization and Crime Nexus? (Case Study: Iranian Provinces)

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ABSTRACT

However, urbanization can have positive effects on the labor force and economic growth in urban areas the unplanned and rapid pace of urbanization process can ultimately lead to unpleasant consequences including marginalization, unemployment, poverty, the emergence of slums and shanty towns and the prevalence of crime in urban areas. Therefore, the objective of this study was to investigate the spatial spillover effects of urbanization on crime in 30 Iranian provinces during the period from 2006 to 2015 using dynamic spatial panel data models. The results of the study revealed that urbanization had a positive and statistically significant impacts on crime per capita in Iranian provinces indicating an increase in urbanization enhances the crime level. In addition, unemployment rate, and human capital had significant and negative effects on crime in Iranian provinces, respectively. Finally, the crime per capita in a previous period exerted a significant positive effect on the current crime which stablished the dynamic nature of this phenomenon. Moreover, the results of the study demonstrated that increasing crime per capita in neighboring provinces could elevate the crime in a given province.

1. Introduction

Significant prevalence of crime has always been considered as one of the main concerns in most urban areas which creates an environment of fear,

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insecurity, high socio-economic costs ((Agyei-Mensah et al., 2015; Ghani, 2017). Although researchers have identified various socio-economic, cultural and deterrent variables as the determinants of crime (Aksoy, 2017); many studies introduce urbanization as one of the main factor affecting crime occurrence in delinquent urban settlements (Gumus, 2004; Jalil and Iqbal, 2010; Elis and Liu, 2018; etc). This view about the effects of crime has found many pros and cons during decades and has raised hot debates among scholars about how urbanization affects crime in urban settings. Historically, numerous studies have been globally conducted to determine the direction and the intensity of the mentioned relationship. On one hand, many researchers argued that anonymity among urban dwellers in cities, high population density and less probability of arrest permit the criminals to commit their crime without any fear of recognition (Braithwaite, 1975; Glaeser and Sacerdote, 1999). On the other hand, others believed that at low levels of urbanization, high crime rates may be observed due to the sparsely located residents in an area; meaning that the increase of the urbanization or the size of the city would lead to the reduction of crime level as the result of closer proximity of the residents (Johnson 1992; Spierenburg; 1996, Gaviria and Pages, 2002; Eisner, 2003). Therefore, it can be argued that urbanization may have both negative and positive effects on crime rates depending on the status of the different urban settings. Further empirical investigations are required to establish the universality of the relationship and determine which effect outweighs the other (Gumus, 2004; Malik, 2016).

Moreover, the finding of many theoretical studies indicated that crime may be a phenomenon with dynamic and contagious nature (Lauridsen et al. 2013; Goschin; 2019; Brantingham et al 2020). However, many theoretical studies emphasized the geographical and spatial nature of crime, only a few empirical studies have been conducted about the contagious character of crime and urbanization using geographical and spatial econometric approaches. Neglecting the mentioned properties in studying the relationship between urbanization and crime would lead to the inconsistent and biased estimation of coefficients and ultimately inaccurate and ineffective policy.

Reviewing the literature proved that none of the mentioned studies have applied dynamic spatial econometric approaches to emphasize both the dynamic and spatial nature of crime. As anti-crime and controlling policies are considered as long run policies, they usually can't rapidly reduce the crime level in a one year short term period. Therefore, crime is expected to have a dynamic nature in a region and it also depends on the crime levels in the previous periods. Thus, the dynamic nature of the crime should be taken into account in regional studies (Elhorst, 2012). This can be mentioned as a gap in the literature. Therefore, this study attempted to answer three main questions as its main contributions to the literature. First, this study seeks to determine whether crime is contagious among Iranian provinces or not. Second, taking into account the spatial spillover effects of crime in Iranian provinces, does the dynamic nature of crime matter in defining the relationship between crime and urbanization in Iranian provinces? Third, can we provide any empirical document that the higher level of urbanization in Iran's provinces leads to higher level of crime or vice versa?

The remainder of the paper is organized as follows. After the introduction, Section 2 reviews the theoretical and empirical background of the research. Section 3 describes the methodology, data and the model of the study. Section 4 discusses and interprets the results of the spatial model estimation. Finally, section 5 concludes and provide some policy recommendations.

2. Theoretical background and literature review

2.1. Theoretical background

The economic rationality of crime was primarily introduced by Becker (1968) and Ehrlich (1975). Numerous theoretical reasons have been proposed by different schools and various scholars about the occurrence of crime in urban settlements. Some of the reasons for crime commitment in urban settlements include densely populated areas, size and heterogeneity in cities (Clinard, 1942; Wirth, 1964), rational maximization of utility function as the results of a cost benefit assessment (Becker, 1968), unemployment (Ehrlich, 1973), inappropriate settlement conditions which creates the subculture of violence and poverty (Rogers, 1989), migration of young male individuals with rural family backgrounds (Muggins, 1985), the role of state in defining and creating crime in dependency theory (Rogers, 1989), city size, losing feelings of responsibility by men and anonymity of the criminals in cities (Braithwaite, 1975), lack of social control and deviant climate in large cities (Gumus, 2004), less formal and informal control and social cohesion (Hirschfield and Bowers, 1997), weaknesses of crime control bodies (Soh, 2012), gang operations and unawareness of the citizenship rights or spoon-feeding syndrome, lack of discipline, 'soul destroying' nature of megacities and the "aesthetic wilderness" of the cities (Braithwaite, 1975), increased opportunity to be exposed to deviance and negative effects of criminal behavior (Soh, 2012), law and management issues and freedom of armed uses (Elis and Liu, 2018), plenty of money obtained by crime activities in urban spaces, low probability of arrest, shortage in quality and quantity of security forces and equipment (Aksoy, 2017), congestion of population in city centers (Ghani, 2017).

On the other hand, some of the theories analyze crime in urban areas from three main perspectives which reflect the geographical, social and temporal distribution of crime across society (Brantingham & Brantingham, 1999). Generally, we can classify the history of analyzing the spatial distribution of crime into three main periods. The first period comprises the descriptive studies conducted by Guerry (1833), Quetelet (1847) and Fletcher (1848) and Durkheim (1964) who investigated the differences in crime rates geographically and theoretically stated that property crimes were more prevalent in more densely populated and wealthier areas of the cities. The second period begins in the early years of the twentieth century with Chicago school of thought. The dominant notion in this period was that crime should be considered as the consequence of social disorganization. The researchers used to focus on the spatial clustering of crime in this period

(Brunisma, 2007). The new period of crime geographical and spatial investigation started after a 20 year delay between 1960 and 1980. The empirical studies in this period used to pay a great attention to the geographical distribution of crime in delinquent areas of the megacities (Bottoms et al 2002).

In order to justify and explain the logic for the existence of spatial spillover effects of criminal behavior many studies emphasize on Tobler's first law in geography which argues that "everything is related to everything else, but near things are more related than distance things". Based on the mentioned law the level of crime in one province is strongly affected by the crime level in surrounding provinces (Baller et al, 2001). Moreover various reasons can be represented for the existence of spatial behavior of crime. Anonymity of criminals in the neighboring provinces, learning and peer-group behavior in provinces of a country can be mentioned as reasons for spatial spillover effects of crime between provinces. It should be noted that provinces without common shared borders may have contagious crime as well. Besides, Dong and Torgler (2012) mentioned migration and urbanization as the sociocultural mechanisms for the diffusion of cross-country crime which can cause the expansion of crime through the exchange of ideas, knowledge and common beliefs as a part of social interactions between areas. Regardless of the validity of the mentioned theories and the influencing channel, the urbanization level in different countries may have different effects on the urban crime rate which the direction and the significance of this relationship should be determined based on the empirical studies in different areas of the world (Okafor, 2011).

2.2. Literature review

Although numerous studies have been conducted about the motivations and consequences of crime, no general consensus has been reached about the determinants of crime in societies. The empirical studies about urban crime can generally be classified into three main categories. The first category comprises the descriptive studies about the effects of urbanization on crime (eg. Soh 2012; Esiri, 2016; Dede et al, 2017; Elis and Liu, 2018). The second category includes the studies which investigated the effects of urbanization on crime using traditional methods or conventional non-spatial econometric models (for instance, Glaeser and Sacerdote, 1999; Gumus, 2004; Jalil and Iqbal 2010; Malik, (2016), Ghani, 2017; Nguyen, 2019; etc). The third group of the studies examined the factors affecting the spatial patterns of urban crime and the determinants of geographical distribution of crime in urban agglomerations using geographical or spatial econometrics approaches (Anselin et al., 2000; Lauridsen et al., 2013; Dutkowska and Leitner, 2017; Aksoy, 2017). The characteristics of the empirical studies using econometric approaches were presented in Table (1).

Table 1. The summary of studies about the relationship between urbanization and crime using non-spatial econometric approaches

Author	Countries	Period	Methodology	Findings
Buonanno and Montolio (2008)	Spain	1993-1999	FE/GMM	$\mathrm{C}(-1) \to^{+} C, \mathrm{Ub} \to^{+} C$, $For \to^{+} C$, $\mathrm{ClR} \to^{-} C$, $YUne \to^{+} C$, $Edu \to^{-} C$, $\mathrm{Con} \to^{\mp} C$, $GDPPC \to^{+} C$, $GR \to^{-} C$
Dutta and Husain (2009)	India	1995-2005	SUR	$\mathrm{Ub} \to^{-} C$, $\mathrm{Lpcdp} \to^{+} C$, $\mathrm{Edu} \to^{-} C$, $\mathrm{Gin} \to^{-} C$, $\mathrm{Pmd} \to^{-} C$, $\mathrm{CVR} \to^{+} C$, $\mathrm{NOP} \to^{-} C$, $\mathrm{IPCPM} \to^{+} C$, $\mathrm{AR} \to^{+} C$
Jalil and Iqbal (2010)	Pakistan	1864-2008	JCT	$\mathrm{Ub} \to^{+} C$, $Une_t \to^{+} C$, $inf \to^{+} C$, $gini \to^{+} C$, $edu \to^{-} C$
Halicioglu et al. (2012)	Japan	1964-2009	ARDL	$\mathrm{LRTEP} \to^{-} LC$, $\mathrm{LTOP} \to^{-} LC$, $\mathrm{LUb} \to^{+} LC$, $\mathrm{LDR} \to^{+} LC$, $\mathrm{LUne} \to^{+} LC$
Fetros et al. (2012)	30 Iranian provinces	2006-2008	panel data approach	$\mathrm{Ub} \to^{+} C$, $\mathrm{Une} \to^{+} C$, $Pov \to^{+} C$

Author	Countries	Period	Methodology	Findings
Bharadwaj (2014)	India	2001-2007	OLS	Ub $\rightarrow^{+} C$, $Ineq \rightarrow^{+} C$, Une $\rightarrow^{-} C$, $Edev \rightarrow^{-} C$, $edu \rightarrow^{-} C$, $Pov \rightarrow^{+} C$, $GDP\ growth \rightarrow^{+} C$, Lsq $\rightarrow^{-} C$
Ansari Samani & Roozbehani (2018)	Iranian provinces	2000-2014	GMM	Une $\rightarrow^{+} C$, $Ub \rightarrow^{+} C$, $GDPPC \rightarrow^{+} C$, Gs $\rightarrow^{-} C$
Nguyen (2019)	Indonesia	2007-2012	GMM	Ub $\rightarrow^{+} C$, $males \rightarrow^{-} C$, $pop \rightarrow^{+} C$, $gini \rightarrow^{+} C$, $edu \rightarrow^{-} C$, $Pov \rightarrow^{+} C$, $GDP\ growth \rightarrow^{+} C$, $LnPCE \rightarrow^{+} C$
Oyelade (2019)	Nigeria	1990-2014	ARDL	GDPPC$\rightarrow^{-} C$, HEdu $\rightarrow^{-} C$, Up $\rightarrow^{+} C$, LRp $\rightarrow^{+} C$, Une $\rightarrow^{-} C$, $Pov \rightarrow^{+} C$, $UF \rightarrow^{-} C$, UM $\rightarrow^{+} C$
Soleimani Magham et al. (2019)	Iranian province	2008-2018	GMM	HEdu $\rightarrow^{-} C$, Mis $\rightarrow^{+} C$, GDPPC $\rightarrow^{+} C$, $popg \rightarrow^{+} C$, $Ub \rightarrow^{+} C$, Gini $\rightarrow^{-} C$, Gini$^{2} \rightarrow^{+} C$

Source: mentioned studies

Variables: C crime, LC logarithm of crime, Ub urbanization rate, pop population, Bpop black population, Une unemployment, GDPPC gross domestic product per capita, Inf inflation, Edu education, Pov poverty, Inq inequality, males number of males aged (15-25), Lsq law system quality, PCE per capita expenditure, RGDPPC real gross domestic product per capita, UR unemployment rate, SE secondary enrolment, PD population density, NoCS number of cases solved, Edu education, PCR property crime rate, NCR crime against individuals, NCC number of convicted cses, RtP report to police, LPCI logarithm of per capita income, LDET logarithm of deterrence variable, Lune logarithm of unemployment rate, , LEdu logarithm of education, LC logarithm of crime, LRTEP logarithm of real total expenditure on policing, LTOP logarithm of total number of police, LDR divorce rate, Lune, Yune youth unemployment, For foreigners, GR growth rate, Con condemn rate, ClR clearance rate, Lpcdp logarithm of per capita SDP, Gin gini coefficient, Pmd number of police officers, IPCPM number of penal code per civil policeman, , AR number of arrests in previous period, CVR conviction rate in previous period, HEdu higher Education, Up urban population, Rp rural population, UF unemployment (female), UM (male), POVR poverty rate, Gs government size, Mis misery index, Popg population growth, $\mathbf{Gini^2}$ gini index squared.

Methods: OLS Ordinary Least Square, JCT Johansen Cointegration Technique, ARDL Autoregressive Distributed Lags, D-GMM Difference-Generalized Method of Moments, PD panel data, FE fixed effect, SUR seemingly unrelated regression.

Results: $\rightarrow^{+}$=positive relationship, $\rightarrow^{-}$=positive relationship

Reviewing the studies conducted about the effects of urbanization on crime indicated that none of the previous empirical researches was conducted about the effects of urbanization on crime taking into account both the spatial spillover effects and dynamic nature of crime in urban areas using dynamic spatial econometric approaches. Ignoring the dynamic character and spatial spillover effects in investigating the relationship between urbanization and crime can lead to bias estimations of the parameters and wrong policy recommendations by urban planners. Although a few studies have mentioned spatial patterns and spatial consequences of crime, none of them have investigated the spatial on crime paying attention to both the dynamic and the spatial characteristics of crime in regional level. The mentioned point can be considered as the main contribution of this research to the literature. The summary of the studies conducted about crime using spatial panel data approach can be obtained in Table (2).

Table 2. The list of the studies about crime using spatial econometric approaches

Author	Country/ region	Period	Method	Findings
Hooghe et al. (2011)	Belgium	2001-2006	SEM	POPD $\rightarrow^{+} C$, LMI $\rightarrow^{-} C$, LUne $\rightarrow^{+} C$, Yo $\rightarrow^{-} C$, LNNr $\rightarrow^{+} C$, TA $\rightarrow^{+} C$, Gini $\rightarrow^{+} C$
Pavlo (2011)	Ukrine	2003-2006	SLM/SLM	Ub $\rightarrow^{+} C$, Mor $\rightarrow^{+} C$, GRP $\rightarrow^{+} C$, Detr $\rightarrow^{+} C$, Yo $\rightarrow^{+} C$, Ineq $\rightarrow^{+} C$, Une $\rightarrow^{-} C$, Edu $\rightarrow^{+} C$
Lauridsen et al. (2013)	15 EU-Countries	2000-2007	SEM	GDPG $\rightarrow^{-} LC$, POP $\rightarrow^{+} LC$, LPEdu $\rightarrow^{-} LC$, URP $\rightarrow^{+} LC$, INF $\rightarrow^{+} LC$
Farahmand et al. (2016)	Iran	2006-2011	SEM	**Dependent variable:** Robbery Une $\rightarrow^{+} C$, Ub $\rightarrow^{+} C$, Ind $\rightarrow^{-} C$, Gini $\rightarrow^{-} C$
				Dependent variable: Suicide $GDPPC \rightarrow^{+} C$, $PI \rightarrow^{-} C$
Goschin (2019)	Romania	2015	GWR	GDP $\rightarrow^{-} C$, Une $\rightarrow^{-} C$, Ub $\rightarrow^{+} C$

3. The model specification, data and econometric methodology

3.1. Model specification

Due to the dynamic nature of the crime, the lagged value of the crime in the previous periods was included in the empirical model. Thus, the relationship between crime, urbanization, human capital, unemployment and real GDP per capita was specified as follows:

$$\begin{aligned} LCPC_{it} = \beta_0 + \beta_1 LCPC_{it-1} + \beta_2 \sum_{j=1}^{n} W_{ij} LCPC_{jt} + \beta_3 LUR_{it} \\ + \beta_4 LH_{\ it} + \beta_5 LGDP_{\ it} + \beta_6 LUNE_{\ it} + \mu_i + \varphi_{it} \end{aligned} \quad (1)$$

Where LCPC represents the logarithm of crime per capita for ith province in year t and $LCPC_{it-1}$ shows the level of the logarithm of crime per capita in the previous year. LUR_{it} is the logarithm of urbanization rate. LH_{it} and $LGDP_{it}$ represent the logarithm of human capital and logarithm of real GDP per capita in province i in year t, respectively. $LUNE_{it}$ stands for the logarithm of unemployment rate for the ith province in year t. Ceteris paribus, any of the $\beta_1,\ldots \beta_7$ coefficients measures the size of the effect for the corresponding explanatory variable on crime per capita in the Iranian provinces and $\sum_{j=1}^{n} W_{ij}LCPC_{jt}$ illustrate the spatial lag of the dependent variables (crime per capita) as the spillover effect. In defining the spatial spillover effect, Elhorst (2014) stated that changes in a particular explanatory variable in a certain unit can change the dependent variable in that unit as well as the dependent variable in other units. Moreover, φ_{it} is the disturbance term and W_{ij} represents the element of the ith row and jth column in the spatial weighting matrix.

In the spatial weighting matrix, the weights values were determined based on the contiguity or the distance between spatial units. It should be noted that the weight matrix was constructed based on geographical latitudes and longitudes of the locations (not proximity) because studies dealing with geographical units and spatial proximity usually use a binary contiguity matrix in which elements $W_{ij} = 1$ if two specific observation share common borders and $W_{ij} = 0$ otherwise (Vega and Elhorst, 2013). In other words, a spatial unit affects the other spatial unit or absolutely not. Therefore, the mentioned criterion restricts the interaction between observations only to those units which share common borders. Following Tobler's prominent first law in geography which states that “Everything is related to everything else, but near things are more related than distant things”, in constructing the weight matrices, it is recommended to use the distance between the observations instead of merely paying attention to the proximity and sharing common borders (Kukenova and Monteiro, 2009). The elements of the weight matrix were obtained based on the distance criterion as follows:

$$W_{ij} = \begin{Bmatrix} \frac{1}{d_{ij}} & i \neq j \\ 0 & i = j \end{Bmatrix} \quad (2)$$

Where d_{ij} is Euclidean distance between the two provinces i and j calculated based on coordinates (latitudes and longitudes).

3.2. Methodology

3.2.1. Cross-sectional dependence

The cross-sectional dependency (CD) can be tested using an alternative statistic that is presented in Equation (3).

$$CD = \sqrt{\frac{2T}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \right) \quad (3)$$

For values of N and T tending to ∞ ($N \to \infty$ and $T \to \infty$) in any order $CD \xrightarrow{d} N(0,1)$ under the H_0 hypothesis of no-cross sectional dependence where $\hat{\rho}_{ij}$ shows the joint correlation coefficient between variables (Hoyos and Safidis, 2006).

3.2.2. Panel unit root tests

In order to detect the stationarity of the variables the Hadri and Rao (2008) panel unit root test was conducted. The advantage of this panel unit root test in comparison with the alternative tests refers to the capability of the mentioned test that takes into account various types of structural breaks in data under the null hypothesis. The calculated statistic for Hadri and Rao (2008) unit root test is determined as follows:

$$LM_{T,N,K}(w) = \frac{1}{N} \sum_{i=1}^{N} \mu_{i,T,k} \, (w_i) \quad (9)$$

Where $\mu_{i,T,k}(w_i) = \frac{\sum_{t=1}^{T} S_{it}^2}{T^2 \hat{\sigma}_{\varepsilon,i}^2}$, S_{it}^2 stands for the partial sum of residuals and $\hat{\sigma}_{\varepsilon,i}^2$ represents the long run variance estimator of ε_{it} (Hadri and Rao, 2008).

3.2.3. Spatial correlation test

One of the most frequent indices which is commonly used for testing spatial correlation is Moran's I statistic. The Moran's I index can be formulated as equation (10).

$$I = \frac{N \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{(\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}) \sum_{i=1}^{n} (x_i - \bar{x})^2} \qquad (10)$$

In Equation (10), x_i denotes the mean of variable, x_i and x_j represent the magnitude of the variable at the ith and jth locations, respectively. In this equation, w_{ij} shows the spatial weight between ith location relative to jth. Moreover, N is the number of provinces refers to the number of provinces and equals to 30 in this research. Positive values for Moran's I statistic ($I > 0$), demonstrates positive spatial autocorrelation meaning that the provinces with low and high levels of crime per capita are contiguous to each other. On the other hand, A negative value of Moran I statistic ($I < 0$) indicates the negative spatial autocorrelation and dissimilarity of the contiguous provinces. When the Moran's I statistic equals to zero, it can be concluded that the crime per capita is randomly distributed among provinces (Salima and Bellefon, 2018).

3.2.4. Spatial econometric models (SYS-GMM)

The most general vector form of a dynamic panel model in space and time can be expressed as Equation (12).

$$Y_t = \delta Y_{t-1} + \rho W_{1t} Y_t + EX_t \beta + EN_t \gamma + \mu_t + \varepsilon_t \qquad (12)$$

Where $\varepsilon_t = \varphi + \lambda W_{2t} \varepsilon_t + u_t$ and$t = 1, \ldots, T$. In Equation (12), Y_t stands for a $N \times 1$ vector constituted of observations of dependent variables for every spatial unit for $i = 1, \ldots, N$ and$t = 1, \ldots, T$. In this equation, W_{1t} and W_{2t} represent $N \times N$ non-stochastic and exogenous spatial weight matrices. φ and μ show country and time effect vectors, respectively. The exogenous explanatory variables of the model are defined by a $N \times p$ matrix namely EX_t $(p \geq 0)$ while the endogenous explanatory variables with respect to the dependent variable (Y_t) are described by a $N \times p$ matrix namely EN_t $(q \geq 0)$. Ultimately, we take this basic assumption that u_t is a normally distributed variable with zero mean and variance Ω ($u_t \sim \mathrm{N}(0, \Omega)$. Finally, the model which includes the both time and space effects simultaneously can be specified as follows:

$$Y_t = \delta Y_{t-1} + \rho W_{1t} Y_t + EX_t \beta + EN_t \gamma + \varphi + \mu_t + u_t \tag{13}$$

In this model, the estimated spatial lag coefficient determined the positive or negative impacts of Y_t which are created by close locations (Kukenova and Monteiro, 2009). In this situations, the least square estimator would be biased and other estimators should be applied. In this circumstances, due to the occurrence of endogeneity issue it is usually recommended to use System-Generalized Method of Moments (System-GMM) approach in spatial panel data to estimate unbiased and consistent coefficients (Zhou and Wang, 2018).

3.3. Data

This study used the annual data from 30 Iranian provinces during the period from 2006 to 2015. Data was collected from the statistical yearbooks published annually for Iranian provinces by Iranian Statistical Centre (www.amar.org.ir). The human capital index was the average of years of schooling, calculated as follows:

$$\mathrm{AYS_t} = \sum_{\mathrm{j}} \mathrm{YR_j} \,.\, \mathrm{HS_{jt}} \tag{8}$$

Where $\mathrm{AYS_t}$ is average of years of schooling in the year t, $\mathrm{YR_j}$ is number of years needed to obtain the degree j, and $\mathrm{HS_{jt}}$ is the percentage of the population who received j as their highest degree in the year t. The summary statistics and the definition of variables were presented in Table (3). It should be mentioned that all the variables were included in logarithmic form to the model making it possible to interpret the estimated coefficients as elasticity.

Table 3. Definitions of key variables and their summary statistics

Variables	Symbol	Unit	Obs	Mean	Std. dev
Crime per capita	CPC	Number *per* 10,000 population	300	105.32	111.651
Urbanization	UR	Percentage of the urban population in the total population	300	65.09	12.045
Human capital	H	average years of schooling	300	8.799	9.976
Unemployment	UNE	Percentage of unemployed workers in the total labor force	300	11.43	2.868
GDP per capita	GDP	Constant 2011 thousand million Rials per capita	300	159613.7	439214.8

Source: Authors' calculations

Figures (1) and (2) illustrate the changes of crime per capita patterns in 2006 and 2015.

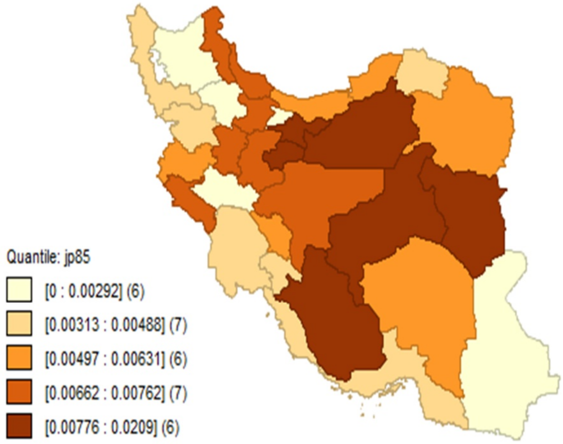

Figure 1. Crime per capita in Iranian provinces (2006)

Source: Authors' calculations

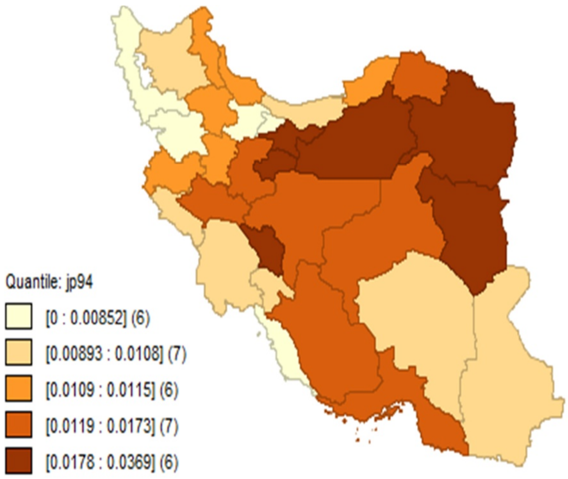

Figure 2. Crime per capita in Iranian provinces (2015)

Source: Authors' calculations

The highest values of per capita crime rates were observed during 2006 to 2009 and 2014 in South Khorasan province. On the other hand, the highest per capita crime rate during 2010 to 2013 and 2015 can be attributed to Semnan province.

4. Empirical results and findings

4.1. Cross-sectional dependence

In order to detect the cross-sectional dependence, the Pesaran's CD test (2004) was used. The CD statistic is calculated under the null hypothesis of cross-sectional independence. In panel data approach, the CD statistic for each variable asymptotically follows a two-tailed standard normal distribution. The test results were illustrated in Table (3).

Table 4. Results of Pesaran's CD test for cross-sectional dependence

Variables	Statistics	P-value
LCPC	51.34	0.000
LUR	44.08	0.000
LH	16.01	0.000
LUNE	8.53	0.000
LGDP	64.87	0.000

Source: Authors' calculations

According to the results of Table (4), as the p values calculated for all the variables were less than 0.05, the null hypothesis of the cross sectional independence in Pesaran's CD test was rejected meaning that all the variables were cross-sectionally dependent. The mentioned results provide enough evidence to ensure about the presence of cross-sectional dependence among the variables of the model.

4.2. Panel unit root test

Given the cross-sectional dependence among observations, it is possible to use a second-generation panel stationary test for determining the integration properties of the variables in order to take into account the unobserved heterogeneity in potential structural breaks and to further control the sectional dependency among spatial units simultaneously and serial correlation in errors, the Hadri and Rao (2008) panel unit root test was conducted under the null hypothesis of the stationarity of variables. Implementing this test makes it possible to analyze the fluctuations of the variables and determine whether the effects of the variable shocks are permanent or not. The results of Hadri and Rao (2008) were reported in Table (5).

Table 5. The results of the Hadri and Rao (2008) panel unit root test

Variables	Critical values for different confidence level				P value	HR statistic	Result
	90%	95%	97.5%	99%			stationary
LCPC	14.57	18.10	21.75	26.32	1.00	0.755	stationary
LUR	12.3	15.01	21.28	23.22	1.00	0.871	stationary
LH	4.79	5.67	6.59	7.67	1.00	0.278	stationary
LUNE	13.50	18.10	21.65	26.33	1.00	0.754	stationary
LGDP	9.96	12.14	15.77	20.62	1.00	0.555	stationary

Source: Authors' calculations

Based on the results of the Hadri and Rao (2008) panel unit root test, as the p values were larger than 0.01, the null hypothesis for the stationarity was not rejected in all levels of critical values. Therefore, the stationarity of all the variables is confirmed.

4.3. Moran's I statistics

Spatial autocorrelation is interpreted as the greatest similarity of closer objects values in proximity of each other in comparison to the distant objects values which causes the emergence of spatial clusters (Zhao et al., 2017). The most common statistic which is utilized for the detection of spatial autocorrelation is Moran's I statistic. The results of the Global Moran's I statistic (1950) were presented in Table (6).

Table 6. Global Moran’s I statistics for crime per capita

Year	Moran’s I value	*p*-value
2006	0.03	0.12
2007	0.035	0.12
2008	0.039	0.43
2009	0.06	0.14
2010	0.266	0.005
2011	0.237	0.007
2012	0.178	0.01
2013	0.118	0.039
2014	0.119	0.04
2015	0.149	0.02

Source: authors' calculations

As it can be seen in Table (6), the Global Moran’s I statistics were positive for all years and were statistically significant for the period from 2010 to 2015 which provides evidence for the presence of spatial dependency among Iranian provinces. Although, the magnitude computed for Global Moran's I statistic can be considered as an appropriate measure to determine the general trend of spatial dependency, it provides no information about those provinces which do not follow the mentioned general trend. Therefore, the Local Moran's I statistic proposed by Anselin (1995) is commonly used for a more accurate examination. The results of the Local Moran's I statistic were provided in Figures (3) and Figure (4).

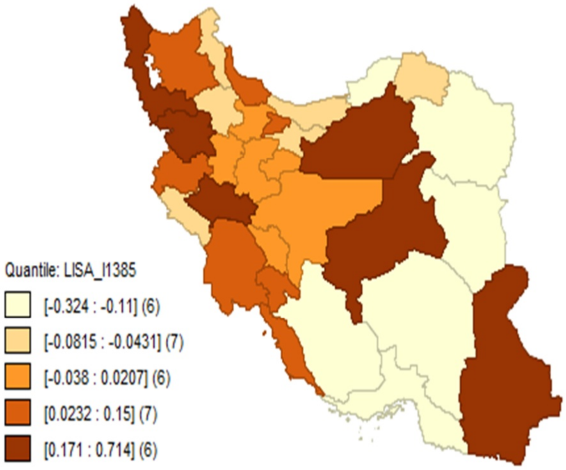

Figure 3. Local Moran map for crime per capita in Iranian provinces, 2006

Source: Authors' calculations

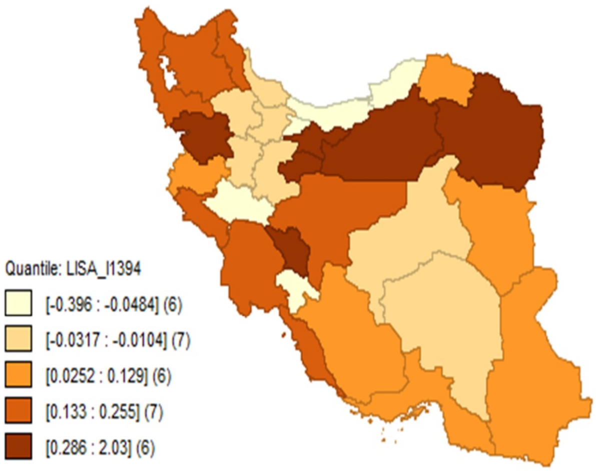

Figure 4. Local Moran map for crime per capita in Iranian provinces, 2015

Source: Authors' calculations

In 2006, 19 out of the 30 Iranian provinces exhibited a positive spatial autocorrelation between the crime per capita in one region and those in other regions. The positive Moran's I statistic confirmed that provinces with a high level of crime per capita are contiguous to one another; the same holds for provinces with a low level of crime. In 2015, 17 of the examined provinces exhibited positive correlation coefficients.

5. Results of the model estimation

The empirical model of the study for the investigation of the spillover effects of urbanization on crime in Iranian provinces was estimated using both System GMM and Spatial System GMM approach. For the better comparison of the results, the values of the estimated coefficients using System GMM approach were provided as well; however, the effects of spatial interaction between the variables were unaccounted for in the system GMM model. Consequently, the results of system GMM approach are unreliable given the potential bias in the estimated coefficients.

Table 7. The results of the spatial model estimation taking into account the spillover effects of urbanization on crime

Variables	SYS-GMM		Spatial SYS-GMM	
	Coefficient	t-statistic	Coefficient	t-statistic
$LCPC_{it}$ (-1)	0.620***	36.55	0.581***	39.41
LUR_{it}	1.842***	11.15	0.890***	3.59
LH_{it}	-0.097***	-3.07	-0.119***	-3.99
$LUNE_{it}$	0.148***	3.28	0.127 ***	3.73
$LGDP_{it}$	0.131 ***	4.57	-0.110 ***	-6.73
$W * LCPC$			0.085***	19.01
constant	-11.045 ***	-21.80	-3.055***	-3.19
R^2			0.96	
R^2Adjusted			0.96	
Wald Test	5688.20***		8261.16 ***	
F- Test			1376.86 ***	
Sargan Test	28.55 (1.00)		25.782 (1.00)	

Source: Authors' calculations

Note: ***, ** indicate 0.01 and 0.05 level of significance, respectively.

Table (7) presents the results of the estimation for the empirical model to investigate the relationship between crime and urbanization taking into account the spatial dependence using dynamic spatial panel data approach. As the study model was estimated in a logarithmic form all the coefficient values can be interpreted as elasticity with respect to the corresponding variable. Based on the obtained results, all the estimated coefficients of the model were statistically significant. Generally, the existence of spatial spillover effect was confirmed among Iranian provinces which demonstrated that increasing crime per capita in neighboring provinces could elevate the crime in a given province.

The estimated coefficient for the lagged logarithm of crime per capita found to be positive and statistically significant asserting that the values of crime per capita in the previous periods can significantly and positively affect the logarithm of crime per capita in the current period. This finding could have connotations that ceteris paribus, 1% increase in the logarithm of crime per capita in the previous period can increase the current value of logarithm of crime by 0.581 % which confirms the dynamic characteristic of crime. This finding emphasizes on the long run requirements of anti-crime policy making. It can be asserted that the elasticity of logarithm of crime in the current period with respect to the logarithm of crime in the previous period was equal to 0.581.

On the other hand, the coefficient estimated for logarithm of urbanization (LUR_{it}) was positive and statistically significant indicating the positive and statistically significant impact of urbanization on crime in Iranian provinces. This result provide enough evidence to establish the positive impacts of urbanization process on committed crime in Iranian provinces expressing that the more the urbanization, the more the crime level. Ceteris paribus, taking into account the spatial spillover effects of crime, it was revealed that 1 percent increase in the logarithm of urbanization magnitudes in Iranian provinces tends to increase the logarithm of crime per capita by 0.890 %. In other words, the elasticity of crime with respect to the urbanization was equal to 0.890. Therefore, a part of the crime fluctuations in Iranian cities could be explained by urbanization phenomenon in Iranian provinces. This finding is in line with the results of studies carried out by Jalil and Iqbal (2010), Palvo (2011), Lauridsen et al. (2013), Bharadwaj (2014), Nguyen (2019) and Goschin (2019).

Based on the results of the model estimation, logarithm of human capital (LH_{it}) seems to exert a negative significant effect on crime per capita in Iranian provinces. Interpreting the results of the estimation it can be stated that 1% increase in human capital could decrease the crime by 0.119 % that emphasizes on the importance of education as the one of the main determinants of human capital in battling against the crime. This result was consistent with the studies conducted by Gumus (2004), Loncher (2007), Bennet, (2018) and Nguyen (2019). Education can be considered as a kind of human capital investment that can considerably increase the future job opportunities. This would lead the marginal returns from doing a profession exceeds that of crime resulting the reduction of criminal incentives (Hjalmarsson and Loncher, 2012). Moreover, human capital can change individuals' preferences through the 'civilization effect'. When an individual who receives higher educational levels will be more reluctant to commit crimes due to psychological restrictions. Human capital paves the way for higher expected income by participating in legal sector as labor force (Bennt, 2018).

Moreover, the estimated value for logarithm of unemployment rate ($LUNE_{it}$) was equal to 0.127 explaining the positive and statistically significant impact of logarithm of unemployment rates on logarithm of crime. In other words, the elasticity of crime with respect to unemployment was equal to 0.127 meaning that 1 percent increase in unemployment would lead to 0.127 percent increase in crime per capita in Iranian provinces. This result was in accordance with the results obtained by Bharadwaj (2014), Elis and Liu (2018) and Nguyen, (2019). Unemployment is usually considered as the main determinant of criminal behavior in societies (Han et al, 2013).

Participation in legal labor force can be seen as the opportunity cost to crime. As an unemployed individual has a low opportunity cost for crime he would have higher incentives to be involved in illegal activities and criminal offences (Hagan, 1993; Wong, 1995). Moreover, some studies introduce a phenomenon titled 'army of idle hands' which encourages large youth population to easily involve in crime activities because of the lack of meeting their expectations. However, some authors believe that crimes are the consequence of unemployment as the low unemployment rate functions as a strong driving force for criminals and cause higher tendency to do violence to obtain a lot of money (Blackmore, 2003). This finding confirms the results obtained by previous studies including Hooghe et al. (2010), Pavlo (2011), Bharadwaj (2014), Oyelade (2019) and Andresen et al. (2021).

Additionally, the estimated value for logarithm of real GDP per capita ($LGDP_{it}$) was equal to -0.110 expressing negative and statistically significant impact of economic development on crime committed in urban areas in Iranian provinces. GDP per capita is an economic determinant of crime that can be interpreted as the general level of prosperity in a certain province (Buonanno and Montolio, 2008). Higher standard of living and greater economic welfare reduce people incentives to contribute in crime activities (Hazra and Cui, 2018).

Finally, the spatial autoregressive coefficient $W * LCPC$ was equal to 0.085 which demonstrates the spillover effects of crime in the neighboring provinces on the crime level of the corresponding province. Interpreting this result it can be suggested that the increase of the crime levels in neighboring provinces tend to enhance the crime level in Iranian provinces. This issue can be attributed to the deep-routed geographical, socioeconomic, cultural and regional links between the Iranian provinces. Besides, anonymity of criminals in neighboring provinces can be mentioned among other reasons. The results of the Wald's test statistic confirmed the whole significance of the estimated model. The Sargan test is also used to make sure about the appropriateness of the instrumental variables in GMM approach which is conducted on the null hypothesis of the validity of the selected instrumental variables. The calculated test statistic of the Sargan test confirmed the validity of the instruments in estimating the model as well.

6. Discussion and conclusion

Crime is always considered as a phenomenon which creates distortions, anxiety, less integration and destabilization of urban life as well as destruction of the sense of security for urban residents leading to huge socio-economic costs. Although previous studies have mentioned the theoretical impacts of urbanization on crime, no investigation has been carried out on the various channels through which urbanization can affect crime taking into account both the dynamic and spatial spillover effects of crime. Due to the long run characteristics of anti-crime policies, neglecting the dynamic and spillover effects of crime can cause the biased estimation of the coefficients resulting inaccurate conclusions and wrong policy recommendations. Thus, the purpose of this study was to explore the effect of urbanization on crime incidence in Iranian provinces taking into consideration both the dynamic and spatial natures of crime offences using spatial system-GMM approach during the period from 2006 to 2015 in order to fill the mentioned research gap. The main conclusion of this paper can be stated in a unique phrase: both spatial and dynamic features of crime matter in developing crime prevention strategies in Iranian provinces. The findings of the study approved that the crime in a previous period exerted a significant positive effect on the crime in a current period, indicating that crime followed a dynamic pattern. On the other hand, the results of the model estimation proved the positive and statistically significant impacts of urbanization on crime per capita in Iranian provinces indicating that increase in urbanization can increase crime significantly. Moreover, the negative impact of education and real GDP per capita on committing crime were confirmed. On the other hand, as it was expected based on theoretical background, unemployment had a positive and significant effect on crime level in Iranian provinces. The spatial autoregressive coefficient associated with W*LCPC was positive and statistically significant. Accordingly, increasing crime in a neighboring province would elevate the crime of corresponding province.

The main recommendation of this study is to warn and inform local authorities about the negative and destroying effects of unplanned urbanization process. If real actions aren't taken in this regard, the migration flows from rural areas to urban settlements in seek of higher expected income or higher standard of living can inevitably create unfortunate and unpleasant consequences including horrible statistics about current marginalization issues and uninhabited villages, the emergence of slums and shanty towns, environmental degradation and higher crime rates in Iranian megacities as the apparent result of this process. Planning some urban regulations for land use and determining some green belt restriction or specific districts with higher chance of employment for migrants to adjust urbanization into those districts and creating more capacity to justify the huge flows of rapid urbanization can be suggested as other solutions.

Based on the provided evidence on the spatial nature of crime in Iranian provinces, it is highly recommended to planners and policy makers to pay a great attention to simultaneous regional development polices in Iranian provinces to eradicate the socio-economic and prosperity gap between various areas in a region. On one side, balanced development schemes which simultaneously focus on both urban and rural development can have considerable positive consequences for reducing urbanization process and crime level regionally. Focusing on development indices of cities without paying any attention to the development of peripheral rural areas doesn't necessarily bring security and safety for the cities. On the other side, all the security enhancement measures against criminal offences should be planned in a regional scale to pay enough attention to the spatial characteristic of crime in a region. In other words, anti-crime measures should be implemented simultaneously across a regions instead of planning certain security schemes for a city as the most important area of a region. Therefore, it is strongly recommended to planners and policy makers to construct and implement a well-stablished regional anticrime system to considerably increase the controllability of spatial consequences of criminal offences. This should be considered as an effective measure to overcome the contagiousness of crime among Iranian provinces.

According to the positive effects of unemployment on crime per capita, policy makers and planners have to use various capacities of creating job opportunities in rural areas to moderately slowdown the impressive pace of rural-urban migration process in Iranian provinces. Due to the negative effects of education as the main component of human capital on crime adopting special plans for the expansion of practical educations to empower and qualify the migrants in searching job opportunities seems to be crucial in urban areas.

References

Agyei-Mensah, S., Owusu, G., & Wrigley-Asante, C. (2015). Urban health in Africa: looking beyond the MDGs. *International Development Planning Review*, 37(1): 53-60.

Aksoy, E. (2017). Geography of crime and its relation to location: the city of Balıkesir (Turkey). In IOP Conference Series: Materials Science and Engineering (Vol. 245, No. 7, p. 072012). IOP Publishing.

Andresen, M. A., Ha, K., & Davies, G. (2021). Spatially Varying Unemployment and Crime Effects in the Long Run and Short Run. *The Professional Geographer*, *73*(2): 297-311.

Ansari Samani, H., Rouzbahani, M. (2020). Economic Justice and Social Crimes; Some Evidence from Iran's Provinces. *Journal of Economics and Regional Development*, 26(18), 1-18. (in Persian).

Anselin, L. (1995). Local indicators of spatial association—LISA. Geographical analysis, 27(2): 93-115.

Anselin, L. (2009). Spatial regression. *The SAGE handbook of spatial analysis*, *1*, 255-276.

Anselin, L., Cohen, J., Cook, D., Gorr, W., & Tita, G. (2000). Spatial analyses of crime. *Criminal justice*, *4*(2): 213-262.

Anselin, L., Cohen, J., Cook, D., Gorr, W., & Tita, G. (2009). Spatial analyses of crime. Criminal justice, 4(2): 213-262.

Baller, R. D., Anselin, L., Messner, S., Deane, G., & Hawkins, D. (2001). Structural covariates of US county homicide rates: Incorporating spatial effects. *Criminology*, *39*(3): 561-588.

Becker, G. S. (1968). Crime and punishment: An economic approach. In The economic dimensions of crime (pp. 13-68). Palgrave Macmillan, London.

Bennett, P. (2018). The heterogeneous effects of education on crime: Evidence from Danish administrative twin data. *Labour Economics*, 52: 160-177.

Bharadwaj, A. (2014). Is poverty the mother of crime? Empirical evidence of the impact of socioeconomic factors on crime in India. *Atlantic Review of Economics*, 1.

Blackmore, F. L. E. (2003). A panel data analysis of crime in South Africa. *South African Journal of Economic and Management Sciences*, 6(3): 439-458.

Bottoms, A. E., Claytor, A., & Wiles, P. (2002). Housing Markets and Residential Community Crime Careers. *Crime, Policing and Place: Essays in Environmental Criminology*, 118.

Braithwaite, J. (1975). Population growth and crime. Australian & New Zealand Journal of Criminology, 8(1): 57-60.

Brantingham, P. J., Brantingham, P. L., Song, J., & Spicer, V. (2020). Crime hot spots, crime corridors and the journey to crime: An expanded theoretical model of the generation of crime concentrations. In *Geographies of behavioural health, crime, and disorder* (pp. 61-86). Springer, Cham.

Brantingham, P. L., & Brantingham, P. J. (1999). A theoretical model of crime hot spot generation. *Studies on Crime & Crime Prevention*.

Bruinsma, G. J. (2007). Urbanization and urban crime: Dutch geographical and environmental research. *Crime and Justice*, 35(1): 453-502.

Buonanno, P., & Montolio, D. (2008). Identifying the socio-economic and demographic determinants of crime across Spanish provinces. *International Review of law and Economics*, 28(2): 89-97.

Burgess, E. W. (1967 [1925]), 'The Growth of the City: An Introduction to a Research Project', in R. E. Park and E. W. Burgess, eds, The City: Suggestions for the Investigation of Human Behaviour in the Urban Environment, 47–62. Chicago and London: University of Chicago Press.

Clinard, M. B. (1942). The process of urbanization and criminal behavior. *American Journal of Sociology*, *48*(2): 202-213.

Coccia, M. (2018). Violent crime driven by income Inequality between countries. *Turkish Economic Review*, 5(1): 33-55.

Dede, M., Setiawan, I., & Mulyadi, A. (2017, October). Application GIS to Analyse Crime Risk in Bandung. In An Article in the 2nd UPI International Conference of Sociology Education (Vol. 4).

Dong, B., & Torgler, B. (2012). Corruption and social interaction: Evidence from China. *Journal of Policy Modeling*, *34*(6): 932-947.

Dutkowska, N., & Leitner, M. (2017). Land use influencing the spatial distribution of urban crime: A case study of Szczecin, Poland. *ISPRS International Journal of Geo-Information*, 6(3), 74.

Durkheim, E. (1964). *The division of labor* (p. 85). New York: The.

Dutta, M., & Husain, Z. (2009). Determinants of crime rates: Crime Deterrence and Growth in post-liberalized India.

Ehrlich, I. (1973). Participation in illegitimate activities: A theoretical and empirical investigation. *Journal of political Economy*, *81*(3): 521-565.

Ehrlich, I. (1975). On the relation between education and crime. In Education, income, and human behavior (pp. 313-338). NBER.

Eisner, M. (2003). Long-term historical trends in violent crime. *Crime and Justice*, *30*: 83-142.

Elhorst, J. P. (2012). Dynamic spatial panels: models, methods, and inferences. *Journal of geographical systems*, *14*(1), 5-28.

Elhorst, J. P. (2014). Spatial econometrics: from cross-sectional data to spatial panels (Vol. 479, p. 480). Heidelberg: Springer.

Elis, R. J., & Liu, Y. (2018). Human Rights in the Context of Criminal Justice: A Study of Urban Crime. *Open Journal of Political Science*, 8(03): 305.

Erdoğan, S., Dereli, M. A., & Yalçin, M. (2011). Spatial analysis of five crime statistics in Turkey.

Esiri, M. O. (2016). The influence of peer pressure on criminal behaviour. *Journal of Humanities and Social Science*, 21(1): 08-14.

Farahmand, Sh., Saffari, B., & Mousavi, V. (2016). Spatial analysis of the impact of socio-economic factors on crimes in provinces of Iran emphasizing on immigration (2006-2011). *The Economic Research*, 1: 138-117. (In persian)

Fotros M. H., Dalaei Milan A., Ghorbanseresht M. (2012). Effects of Poverty, Unemployment, and Urbanization on Committing Property Crimes in Iran. *Social welfare Quarterly*; 12 (46): :279-317 (in Persian).

Gaviria, A., & Pagés, C. (2002). Patterns of crime victimization in Latin American cities. *Journal of Development Economics*, 67(1): 181-203.

Ghani, Z. A. (2017). A comparative study of urban crime between Malaysia and Nigeria. *Journal of Urban Management*, 6(1): 19-29.

Glaeser, E. L., & Sacerdote, B. (1999). Why is there more crime in cities?. *Journal of political economy*, 107(S6): 225-258.

Goschin, Z. (2019). Local Factors Explaining the Incidence of Criminal Offences in Romania. A Geographically Weighted Regression Model. *Romanian Statistical Review*, (2).

Gumus, E. (2004). Crime in urban areas: An empirical investigation. Akdeniz IIBF Dergisi, 4(7): 98-109.

Hadri, K., & Rao, Y. (2008). Panel stationarity test with structural breaks. Oxford Bulletin of Economics and statistics, 70(2): 245-269.

Hagan, J. (1993). The social embeddedness of crime and unemployment. *Criminology*, 31(4): 465-491.

Halicioglu, F., Andrés, A. R., & Yamamura, E. (2012). Modeling crime in Japan. *Economic Modelling*, *29*(5): 1640-1645.

Han, L., Bandyopadhyay, S., & Bhattacharya, S. (2013). Determinants of violent and property crimes in England and Wales: A panel data analysis. *Applied Economics*, 45(34): 4820-4830.

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.

Hazra, D., & Cui, Z. (2018). Macroeconomic determinants of crime: Evidence from India. *Journal of Quantitative Economics*, *16*(1): 187-198.

Hjalmarsson, R., & Lochner, L. (2012). The impact of education on crime: international evidence. CESIFO DICE Report, 10(2): 49-55.

Hoyos, R. E., & Sarafidis, V. (2006). Testing for cross-sectional dependence in panel-data models. *The stata journal*, *6*(4): 482-496.

Hooghe, M., Vanhoutte, B., Hardyns, W., & Bircan, T. (2011). Unemployment, inequality, poverty and crime: spatial distribution patterns of criminal acts in belgium, 2001–06. *The British Journal of Criminology*, *51*(1): 1-20.

Jalil, H. H., & Iqbal, M. M. (2010). Urbanisation and crime: A case study of Pakistan. *The Pakistan Development Review*, 741-755.

Johnson, E. A. (1992). Cities don't cause crime: urban-rural differences in late nineteenth-and early twentieth-century German criminality. *Social Science History*, *16*(1): 129-176.

Kukenova, M., & Monteiro, J. A. (2009). Spatial dynamic panel model and system GMM: A Monte Carlo investigation (No. 13405). *University Library of Munich, Germany.*

Lauridsen, J. T., Zeren, F., & Ari, A. (2013). A spatial panel data analysis of crime rates in EU. Discussion Papers on Business and Economics.

Department of Business and Economics, University of Southern Denmark, Odense, Denmark.

Lochner, Lance (2007) Individual Perceptions of the Criminal Justice System. *American Economic Review*, 97: 444–460.

Malik, A. A. (2016). Urbanization and crime: a relational analysis. *IOSR Journal of Humanities And Social Science*, 21 (1): 68-74.

Nguyen, H. T. (2019). Do more educated neighbourhoods experience less property crime? Evidence from Indonesia. *International Journal of Educational Development*, 64: 27-37.

Okafor, E. E. (2011). Youth unemployment and implications for stability of democracy in Nigeria. *Journal of sustainable Development in Africa*, 13 (1): 358-373.

Oyelade, A. O. (2019). Determinants of crime in Nigeria from economic and socioeconomic perspectives: a macro-level analysis. *International Journal of Health Economics and Policy*, *4*(1): 20-28.

Pavlo, I. (2011). Distribution of Crime across Ukraine: Panel and Spatial Analysis. *Diss. School of Economics.*

Rogers, J. D. (1989). Theories of crime and development: An historical perspective. The *Journal of Development Studies*, 25(3): 314-328.

Salima, B. A., & Bellefon, M. D. (2018). Spatial autocorrelation indices. *Handbook of Spatial Analysis: Theory Aplication with R*, 51-68.

Soh, M. B. C. (2012). Crime and urbanization: Revisited Malaysian case. *Procedia-Social and Behavioral Sciences*, 42: 291-299.

Spierenburg, P. (1996). Long-term trends in homicide: Theoretical reflections and Dutch evidence, fifteenth to twentieth centuries. *The civilization of crime: Violence in town and country since the Middle Ages*, 63-105.

Vega, S. H., & Elhorst, J. P. (2013). On spatial econometric models, spillover effects, and W. In 53rd ERSA Congress, Palermo, Italy.

Wong, Y. C. R. (1995). An economic analysis of the crime rate in England and Wales, 1857-92. *Economica*, 62(246): 235-246.

Zhou, C., & Wang, S. (2018). Examining the determinants and the spatial nexus of city-level CO2 emissions in China: a dynamic spatial panel analysis of China's cities. *Journal of cleaner production*, *171*: 917-926.

Zhao, J., Wang, Y., & Shi, W. (2017). Using local Moran's I statistics to estimate spatial autocorrelation of urban economic growth in Shandong province, China. In *International Conference on Geo-Spatial Knowledge and Intelligence* (pp. 32-39). Springer, Singapore.