

# The spatiotemporal dynamics and structural covariates of homicide in the Republic of Korea, 2008-2017: A dynamic spatial panel data approach

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## Abstract

This study examined the relationship between the homicide rate and diverse indicators of social disorganization in the Republic of Korea (South Korea) using datasets collected between 2008 and 2017. Due to the statistical limitations of previous homicide research, which used either cross-sectional or longitudinal methodology, this study applied the dynamic spatial panel data model to explore both the spatial and temporal aspects of homicide. The results demonstrate that the homicide rate is spatially and temporally dependent on those of neighbouring units and the time-lagged homicide rate. Moreover, this study found that divorce rate, unemployment rate, number of males in the neighbourhood and ethnic heterogeneity have a statistically significant impact on the homicide phenomenon. This study contributes to the

existing literature by taking a new approach - the dynamic spatial panel data model - to investigate the homicide phenomenon in Korea. In doing so, several suggestions are made for policymakers to respond to homicide rates. Based on the social disorganization theory, these indicators have been found to impact the social network and community members' willingness to engage in social control. This study suggests that customized policies should be implemented to alleviate the level of social disorganization and promote social control over lethal violence.

## Introduction

Although atrocious homicide cases have occasionally attracted nationwide attention in the Republic of Korea (South Korea), homicide has received less academic attention than its counterpart suicide. The discrepancy in attention given to these two types of lethal violence is evidenced by the existing body of research on each. According to the Korea Citation Index (2020), which provides information on all the listed domestic journals and published papers in the country, 4043 studies have been conducted on suicide across all academic disciplines since 2000, whereas only 307 studies have been conducted on homicide within the same period. Part of the reason for this is that the number of suicides per 100,000 was 26.6 in 2018, while it was only 0.8 for homicides according to the Korean Statistical Information Service (KOSIS) (2020). As this difference has been relatively consistent over time, the two topics have attracted disparate levels of attention from the public and academia. Nevertheless, there have been various attempts to examine the homicide phenomenon in South Korea across diverse disciplines, including psychology, sociology and public policy.

Most homicide research in Korea has investigated the individual-level causes of homicides in high-profile cases, whereas few have examined homicide at the structural level. However, in countries where homicide has received more public attention, on both an individual and contextual level, studies on homicide have been widely conducted (Ruther, 2013; Pereira *et al.*, 2017). For example, various studies in the field of criminology have analysed the relationship between homicide and its contextual covariates using different theoretical backgrounds and methodologies (Phillips, 2006; McCall *et al.*, 2010; Nivette, 2011; Ousey and Kubrin, 2014). In particular, social disorganization theorists have investigated the relationship between the homicide rate (HR) and disorganizing social conditions across different geographic areas (Wang and Arnold, 2008; Graif and Sampson, 2009; Ye and Wu, 2011; Ruther, 2013). However, such empirical studies tend to use either a cross-sectional or a longitudinal statistical tool to consider

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the effects of time and space as separate components of the homicide phenomenon (Phillips, 2006; Ye and Wu, 2011).

As consistently noted, the effect of structural covariates of homicide varies in different geographic areas and tends to spread into neighbouring areas; thus, spatial analysis has become an important tool for enhancing inference accuracy and reducing estimation bias (Cohen and Tita, 1999; Baller *et al.*, 2005; Menezes *et al.*, 2013). However, spatial analysis fails to capture the temporal effect that is inherent in this social phenomenon. Thus, in addition to the spatial effect, a growing number of studies have simultaneously examined the temporal dynamics of this phenomenon with ‘the increasing availability of spatial and temporal datasets’ (Ye and Wu, 2011 - p. 800). The spatial panel data model has become a popular approach to examining the spatial and temporal dynamics of diverse social phenomena, including homicide (Ye and Wu, 2011; Ruther, 2013), suicide (Breuer, 2015; Joo, 2017; Yeom, 2021) and other social issues (Baltagi *et al.*, 2012; Bussu *et al.*, 2013). These studies have not only visualized the spatial and temporal patterns of the investigated phenomenon, but also extended ‘modelling possibilities as compared to the cross-sectional setting for spatial data’ (Ye and Wu, 2011 - p. 800). Despite the utility of the model, very few homicide studies that apply the spatial panel data model have been conducted in South Korea. For this reason, this study aimed to explore the spatial and temporal dynamics of the homicide phenomenon in South Korea using the spatial panel data model. More specifically, this study would first visually present the spatial and temporal variations of the homicide phenomenon in Korea with exploratory spatial data analysis (ESDA) techniques. Then, a spatial panel data regression would be performed to examine the impact of social conditions on the HR, while controlling spatial and temporal dependence. By relying on the social disorganization theory, this study primarily examines the effects of deteriorating social conditions on the HR in South Korea.

### Social disorganization theory and homicide rate

With an effort to understand and explain crime at the social level, the social disorganization theory posits that the crime rate is correlated with neighbourhood conditions that are directly and indirectly related to the level of social control over criminal behaviours. Disorganizing social conditions endemic to specific communities are reflected by several social indices, including ethnic diversity, socio-economic status, and residential mobility. Social disorganization theory posits that deviant behaviour is ‘simply the normal responses of normal people to abnormal social conditions’ as noted by Akers (2014 - p. 117). Thus, given that such social conditions usually persist without drastic policy changes, once a deviant behaviour develop in the neighbourhood, it tends to be culturally transmitted from one generation to the next. This theory describes the nature of crime occurrence, which is spatially and temporally dependent and reflective of underlying social conditions (Pereira *et al.*, 2015; Ruther, 2013). Thus, social disorganization theorists have mainly focused on the geographic location and the characteristics persistent there in explanation of crime rates.

Although disorganized social conditions are not the direct cause of deviant action, they cause the breakdown of fundamental social institutions or networks, which eventually makes populations vulnerable to such behaviour. In particular, some social disorganization theorists noted that deteriorating social conditions lower the level of collective efficacy, which represents community members’ ability to intervene in criminal activities (Sampson and Raudenbush, 1997). Hampered informal ability to survey the neighbourhood eventually leads to higher crime rates in a neigh-

bourhood that, in turn, negatively impacts community socialization processes of developing values and moralities among populations in socially disadvantaged neighbourhoods (Sampson, 2011, 2013).

Methodologically, socially disorganized conditions operate with different social indices (McCall *et al.*, 2010). These indices are commonly and closely related to deteriorating social conditions, including low socioeconomic levels, residential mobility, ethnic heterogeneity, family disruption and urbanization, which are assumed to weaken the collective ability to maintain social control (Sampson and Grove, 1989). Several empirical studies have examined the relationship between crime rate and such indices across different regions. They usually find that deteriorating structural conditions are positively associated with crime rates, including the HR (McCall *et al.*, 2010; Ousey and Kubrin, 2014; Pereira *et al.*, 2015). Particularly, these structural conditions are presented with specific indices including divorce rate, percentage of immigrants, employment rate and percentage of the population moving into new geographic areas, indicators assumed to disrupt social communication and networks and negatively influence people’s willingness to engage in collective action against deviant behaviour (Mancik *et al.*, 2018; Pereira *et al.*, 2015). An incapacitated ability to survey and supervise the community eventually impacts the level of crime rate.

In summary, social disorganization theory explains that socially disorganizing conditions endemic and persistent to specific neighbourhoods impact the level of crime by lowering the level of collective efficacy. Previous studies have consistently operationalised the concept of social disorganization using a variety of social indices. Although the association between such indices and HR have been mixed depending on the methodology used by each study, some indices, including the collective level of deprivation and relational breakdown, have been found to have a relatively consistent impact on crime rates, including HR (McCall *et al.*, 2010; Nivette, 2011; Pridemore, 2002). Similar to these previous studies, the current study aimed to analyse the spatial and temporal dynamics of homicide in South Korea by examining the effect of social disorganization indicators on HR using the spatial panel data model.

## Materials and methods

### Data source and measurement

Located in East Asia, South Korea has a total area of 100,300 km<sup>2</sup> with a population of 51.6 million (World Bank, 2019). The geographical units of analysis in this study comprise 240 municipalities, each with an average size of 417.9 km<sup>2</sup> and an average population of 0.21 million. The municipality is roughly equivalent to a town or a city in western Europe and the U.S.

Several datasets publicly available datasets (KOSIS, 2020) were used, *i.e.* for HR (the dependent variable), we used the annual cause-of-death datasets between 2008 and 2017 and as indicators of the level of social disorganization (the independent variables), we used datasets on divorce, ethnic heterogeneity, residential mobility, unemployment and the male population. The homicide rate was measured by the number of homicide per 100,000; the divorce rate was measured by the number of divorced individuals per 1000 people in each municipality; the ethnic heterogeneity was measured by the percentage of the non-Korean population; the residential mobility was measured by the percentage of the population who have come from another municipality; the unemployment rate

was measured by the percentage of unemployed people among the population over 15 years of age; and the male population rate was measured by the percentage of males in the entire population. Datasets on homicide and indicators of social disorganization were collected from the KOSIS database in each municipality between 2008 and 2017. All the datasets per municipality were integrated in a time series during the study period. As there were relatively few homicide incidences; we secured linearity by transforming the observed HR values into their square-roots (Ye and Wu, 2011).

### Analytical strategy

To examine the relationship between the HR and the social disorganization indices, we applied a dynamic spatial panel data model, which controls both the spatial dependence between spatial units and the temporal dependence between time series (Belotti *et al.*, 2016). According to the social disorganization theory, a crime phenomenon persists over a place that is being influenced by the social conditions endemic to said place. Considering the nature of crime occurrence, the temporal dynamics regarding the spatial patterns of crime become a critical aspect of crime analysis (Ye and Wu, 2011). To examine the spatial and temporal aspect of homicide phenomena in South Korea, the dynamic spatial panel data model was applied as follows:

$$Y_{it} = \tau Y_{it-1} + \psi \sum_{j=1}^N w_{ij} Y_{jt-1} + \rho \sum_{j=1}^N w_{ij} Y_{jt} + X_{it}\beta + \theta \sum_{j=1}^N w_{ij} X_{jt} + \mu_i + \varepsilon_{it} \quad (1)$$

where  $Y_{it}$  is the HR in spatial unit  $i$  at the particular time point  $t$ ;  $\tau$  the effect of the lagged HR at  $t-1$ ;  $\psi$  the spatially weighted average

effects of the lagged HR in adjacent spatial units at  $t-1$ ; and  $\rho$  the spatially weighted average effects of the HR in adjacent spatial units at time  $t$ . The spatial weight matrix  $w_{ij}$  is created based on the contiguity of spatial units; with  $\beta$  indicating the effects of the explanatory variable  $X_{it}$ ;  $\theta$  the spatially weighted averaged effects of  $X_{jt}$  in adjacent spatial units;  $\varepsilon_{it}$  the error term; and  $\mu_i$  the fixed-effect variant under the assumption that  $\mu_i$  is correlated with the explanatory variables in the model (Belotti *et al.*, 2016).

In addition to the spatial panel data model, we used several ESDA techniques, including Moran's  $I$  and the local indicator of spatial association (LISA) to visualize HR's spatial and temporal variation. ESDA techniques are types of descriptive analyses that depict the spatial or temporal patterns of the investigated phenomenon before examining the dynamic factors that can explain the causes (Ye and Wu, 2011). For instance, ranging from  $-1$  to  $+1$ , Moran's  $I$  statistic indicates HR's global spatial dependence, while LISA produces a categorical outcome indicating positive or negative clustering at the local level. In this study, we used the *xsmle* command in the Stata software package for dynamic spatial panel data analysis (Belotti *et al.*, 2016) and the QGIS software package for data visualization.

## Results

### Descriptive statistics

The descriptive statistics for each variable is first described (Table 1 and Figure 1). Table 1 averaged all observed values between 2008 and 2017, with Figure 1 presenting observed values

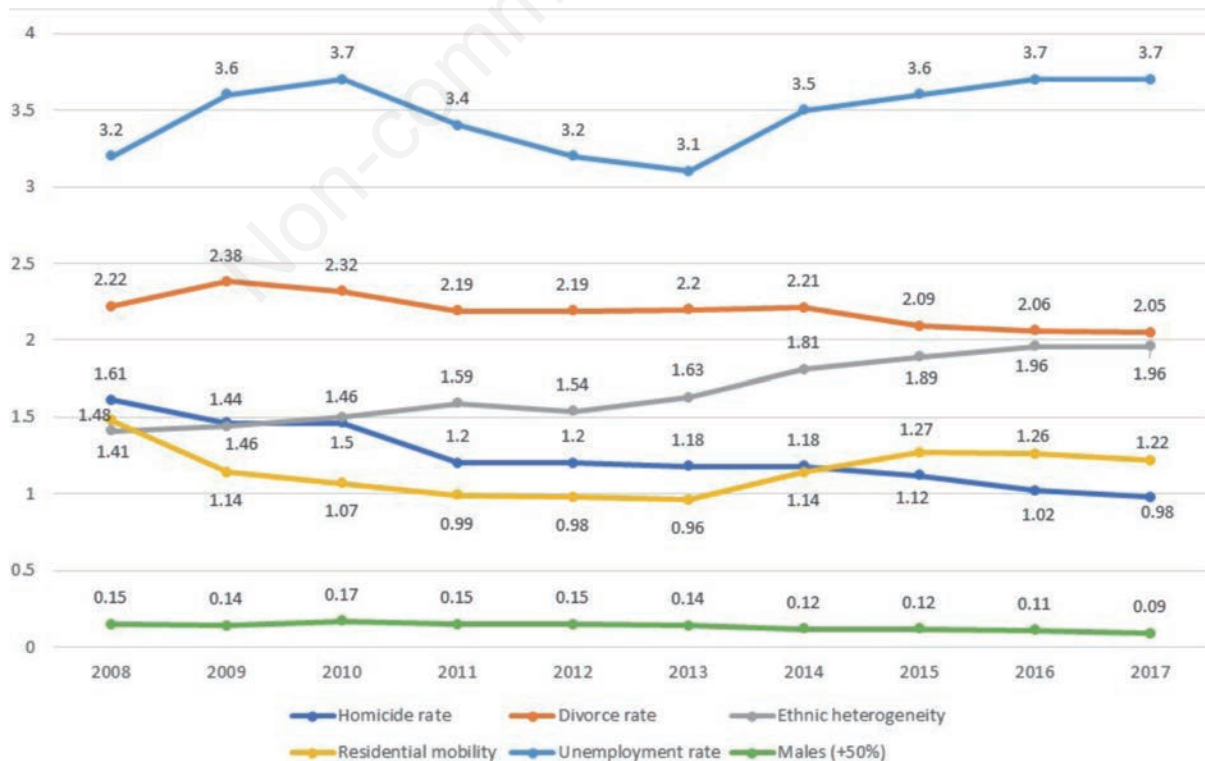


Figure 1. Time series graphs for each variable during the study period.



at each time point. Furthermore, Figure 1 shows that the HR consistently decreased over the study period, falling from 1.61 in 2008 to 0.98 in 2017. Figure 1 also presents that some structural covariates, including divorce rate, residential mobility, and males, decreased while other covariates, including ethnic heterogeneity and unemployment rate, increased with some fluctuation over the study period. Table 1 and Figure 1, in combination, show that homicide and other social disorganization indicators were not evenly distributed, neither spatially nor temporally.

Next, we examined and visualized the spatial distribution of the HR using several ESDA techniques. To this end, the spatial HR distribution over time was explored using a series of thematic maps. As presented in Figure 2, HR was not evenly distributed over the country but locally concentrated. Municipalities in the north-eastern part of South Korea had a relatively high level of HR

as evidenced by the fact that  $HR > 8$  (darkest shade of black in the figure) were most common there. However, this kind of concentration is generally not consistent over time.

Following this, the global spatial dependence among variables was examined over the study period using Moran's  $I$  statistic. Table 2 presents the global spatial dependence at each time point, which shows that the spatial dependence was relatively stable for nearly all variables over time except for HR and residential mobility. A positive Moran's  $I$  indicates that when an observed variable increases within a municipality, those of neighbouring municipalities also increase. However, it should be remembered that this statistic only presents the spatial dependence at the global level without identifying where a statistically significant cluster is located. Thus, this study also examined the clusters of homicide in local units using LISA as seen in Figure 3. Unlike Moran's  $I$  (Table 2),

**Table 1. Descriptive statistics.**

Variable	Minimum	Maximum	Mean	Median	SD
Outcome variable					
Homicide rate (per 100,000)	0.16	14.53	1.23	0.93	1.42
Explanatory variables					
Divorce rate (per 1000)	1.07	3.80	2.15	2.16	0.48
Ethnic heterogeneity (%)	0.29	10.60	1.65	1.17	1.60
Residential mobility (%)	0.01	25.15	1.16	0.74	1.71
Unemployment rate (%)	0.11	7.93	3.52	3.60	0.23
Males (%)	48.93	56.93	50.13	50.03	6.16

SD, standard deviation.

**Table 2. Moran's  $I$  statistics of all variables throughout the study period.**

Variable	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Homicide rate	-0.05	0.02	-0.07	0.01	0.02	0.01	-0.12**	-0.08	0.01	-0.04
Divorce rate	0.40***	0.39***	0.17***	0.26***	0.35***	0.32***	0.32***	0.26***	0.32***	0.27***
Ethnic heterogeneity	0.27***	0.26***	0.26***	0.24***	0.24***	0.25***	0.25***	0.26***	0.28***	0.30***
Residential mobility	0.10*	0.10*	0.10	0.04	0.04	0.15**	0.01	0.03	0.01	0.01
Unemployment rate	0.11*	0.33***	0.05	0.34***	0.26***	0.44***	0.40***	0.32***	0.37***	0.36***
Males	0.37***	0.36***	0.38***	0.39***	0.39***	0.41***	0.42***	0.45***	0.45***	0.45***

\* $P < 0.05$ ; \*\* $P < 0.01$ ; \*\*\* $P < 0.001$ .

**Table 3. Results of the dynamic spatial panel data model.**

Structural covariate	Lagged effect	$X(\beta)$	$WX(\theta)$	SR direct	SR indirect	SR total	LR direct	LR indirect	LR total
HR (t-1) ( $\tau$ )	-0.03	-	-	-	-	-	-	-	-
Weighted HR (t-1) ( $\psi$ )	0.07*	-	-	-	-	-	-	-	-
Divorce rate	-	0.24**	0.08	0.24**	0.05	0.29***	0.24**	0.06	0.30***
Ethnicity Heterogeneity	-	-0.10*	-0.02	-0.10*	-0.01	-0.11**	-0.10*	-0.02	-0.12**
Residential mobility	-	0.01	-0.01	0.01	-0.01	0.00	0.01	-0.01	0.00
Unemployment Rate	-	0.14*	-0.17(*)	0.14*	-0.14*	0.00	0.14*	-0.14*	0.00
Males	-	0.02***	-0.01	0.02***	-0.01	0.01***	0.02***	-0.01	0.01(*)
Spatial variable ( $\rho$ )				0.07***					
Variance				0.38***					
Fixed-effect mean				-0.23					
$R^2$ (within)				0.04					
$R^2$ (between)				0.01					
$R^2$ (overall)				0.01					

HR, homicide rate;  $X(\beta)$ , effect of independent variable;  $WX(\theta)$ , spatially weighted effect of independent variable; SR, sort-run; LR, long-run. (\*) $P < 0.07$ ; \* $P < 0.05$ ; \*\* $P < 0.01$ ; \*\*\* $P < 0.001$ .



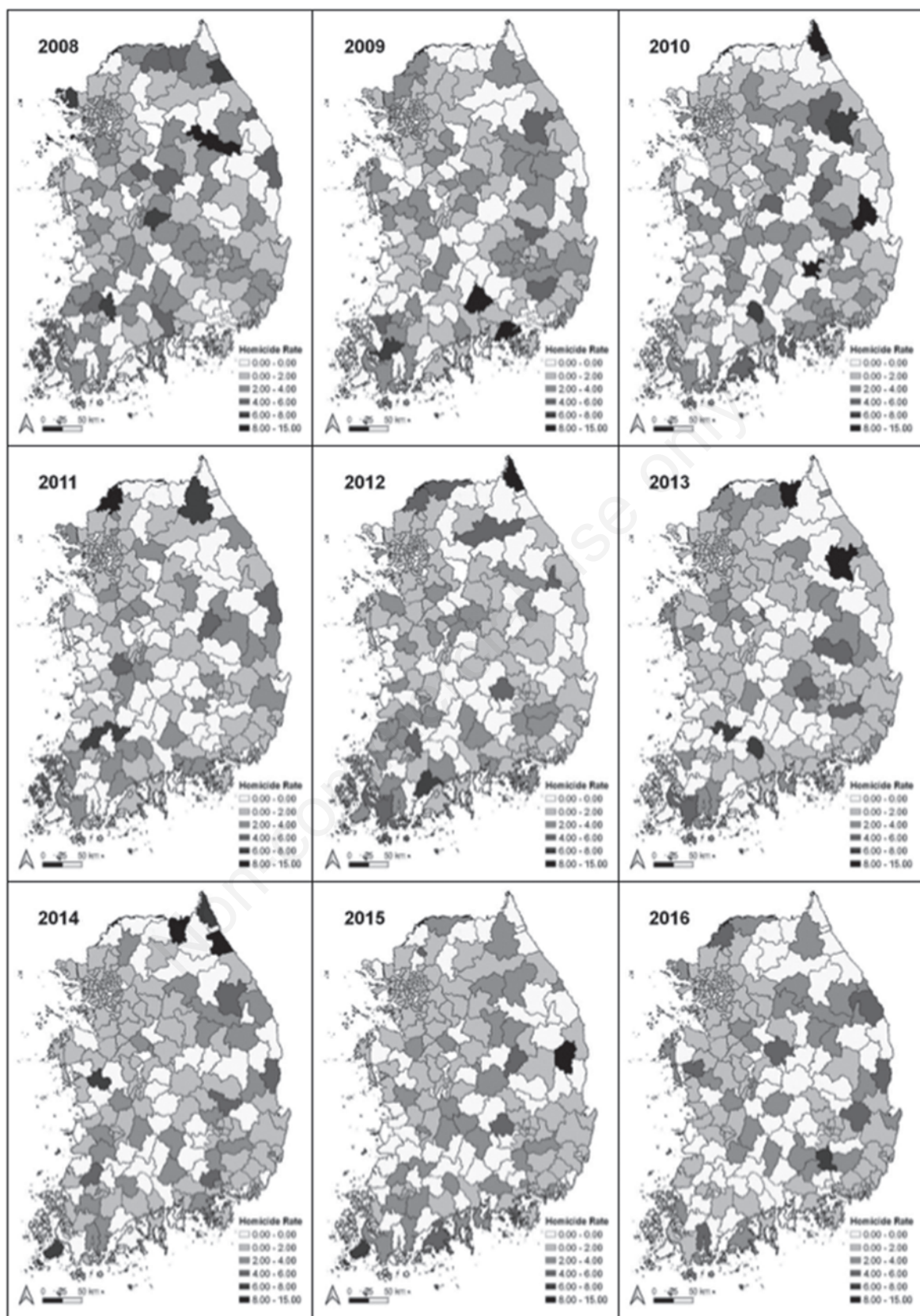


Figure 2. Spatial distribution of the homicide rate during the study period.



the LISA indicators demonstrated that spatial dependence within the HR varies at the local level. The High-High relationship (red colour in Figure 3) indicates a positive and statistically significant association between HR in a municipality and its neighbouring municipality, whereas the High-Low and the Low-High indicate the inverse association. These results also show that, even though the spatial dependence of HR was relatively weak at the global level, the spatial dependence was strong at the local level though not consistent over time. The existence of spatial dependence among variables, as indicated by Moran's *I* and LISA, is not only descriptive, but also appears in the subsequent spatial regression analyses (Porter and Purser, 2010), which indirectly support the application of the spatial panel data model.

### The dynamic spatial panel data model

By applying the dynamic spatial panel data model, this study examined the homicide phenomenon in Korea between 2008 and 2017, while controlling for spatial and temporal dependence. The results are presented in Table 3, which conveys the five estimated parameters, *i.e.* the effect of the lagged HR at  $t-1$  ( $\tau$ ); the spatially weighted average effects of the lagged HR in adjacent spatial units at  $t-1$  ( $\psi$ ); the spatially weighted average effects of the HR in adjacent spatial units at time  $t$  ( $\rho$ ); the effects of the explanatory variable  $X_{it}$  ( $\beta$ ); and the spatially weighted averaged effects of  $X_{it}$  in adjacent spatial units ( $\theta$ ). Table 3 indicates a significant level of spatial and temporal interaction with respect to HR. First, the spatial parameter  $\rho$  shows that a one unit increase in HR of a municipality was associated with a 0.07 unit increase in the spatially weighted average HR of neighbouring municipalities. Furthermore, the two parameters  $\tau$  and  $\psi$  demonstrate that only the spatially weighted average HR had a statistically significant impact on the HR at time  $t$ . These findings demonstrate that a one unit increase in the HR at time  $t$  was statistically associated with a 0.07 unit increase in the spatially weighted average of HR at time  $t-1$ . In summary, spatio-temporal correlation with HR focuses on spatial correlation rather than temporal correlation. HR was shown to relate to past and present phenomena of neighbouring areas rather than to its own past. In other words, HR is a phenomenon that is affected by the surrounding area both statically and dynamically. We also found that the explanatory variables, except for residential mobility, were statistically significant with respect to HR when the spatial or temporal effects of variables were not considered. Parameter  $\beta$  indicates that one unit increase in the divorce rate, unemployment rate and the number of males in the neighbourhood was associated with 0.24, 0.14 and 0.02 unit HR increase, respectively. In contrast, one unit increase in ethnic heterogeneity was associated with a 0.1 unit of HR decrease. Divorce and unemployment, which are proxy variables indicating the degree of family and social disorganization, were identified as social structural factors that affect murder crimes. In addition, the more men in the neighbourhood, the more murder crimes committed there, which can be seen as the result of the overwhelming number of men, who are both perpetrators and victims of murder.

Importantly, when spatial dependence is considered, the effect of each explanatory variable becomes insignificant, as evidenced by the  $q$  parameter. Further, the higher the unemployment rate in the region, the higher the rate of murder; however, the higher the unemployment rate in the neighbourhood, the lower the number of murders. This can be interpreted as that unemployment does not affect the HR in areas where high unemployment rates are prevalent. On the other hand, unemployment increases murder crimes to

some degree in areas where large differences exist in unemployment rates between neighbourhoods, *e.g.*, if the unemployment rate is high in two adjacent areas (A and B), the increase of HR in area A corresponds with its high unemployment rate but the impact is offset by the high unemployment rate in region B. Conversely, if the unemployment rate in area A is high and that of area B is low, the increase in the HR is not offset. Through this phenomenon, we suggest that crime can be triggered not only by the absolute level of social structural disadvantage but also by the relative level.

The dynamic spatial panel data model estimates the short- and long-run marginal effects of explanatory variables on the investigated phenomenon (Belotti *et al.*, 2016). If the first expression below (Eq. 2) is repeatedly replaced with the second one (Eq. 3), the coefficient  $b$  of  $X_{it}$ , the term that affects the dependent variable of the time  $t$ , is the short-run effect and the sum of  $\beta$ ,  $\tau\beta$ ,  $\tau^2\beta$ ... *etc.* is the long-run effect, which is all the coefficients of time  $t$  and  $t-i$  ( $i=1, 2, 3 \dots$  *etc.*). Because the long-run effect is an infinite geometric series, it can be calculated as  $\beta/(1-\tau)$ . However, there was minimal difference between the short- and the long-run effects in this study because  $\tau$ , indicating the temporal correlation, is not significant and low ( $-0.03$ ).

$$(2)$$

$$Y_{it} = \tau Y_{it-1} + X_{it}\beta \tag{3}$$

$$Y_{it-1} = \tau Y_{it-2} + X_{it-1}\beta \tag{4a}$$

$$Y_{it} = \tau(\tau Y_{it-2} + X_{it-1}\beta) + X_{it}\beta \tag{4b}$$

$$= \tau(\tau(\tau Y_{it-3} + X_{it-2}\beta) + X_{it-1}\beta) + X_{it}\beta \tag{4c}$$

$$= \tau(\tau(\tau(\tau Y_{it-4} + X_{it-3}\beta) + X_{it-2}\beta) + X_{it-1}\beta) + X_{it}\beta \dots, \text{etc.}$$

It was evident that HR is influenced by the current, rather than cumulative, social disorganization factors in the region. This contrasts with the accumulated social structural factors (long-run effects) that affect the occurrence of suicide in a previous study (Yeom, 2021). Thus, murder can be interpreted as an accidental and violent crime, while suicide is incited by accumulated disadvantages. The marginal includes direct, indirect and total effects. As evidenced from Table 3, the direct short- and long-term effects of the divorce rate, ethnic heterogeneity, unemployment and the number of males in the neighbourhood were all statistically significant. The four coefficients for the direct effects of these variables were similar to the four coefficients ( $b$ ) at time  $t$  without considering any spatial or temporal effects.

### Discussion and conclusions

The effects of deteriorating, social conditions on HR through social disorganization was examined by the dynamic spatial panel data model in order to control the inherent spatial and temporal dependence in this social phenomenon. The lack of studies on homicide at the contextual level in South Korea encouraged this study, in which we found that the distribution of HR in Korea is both spatially and temporally dependent. It was estimated that HR in a municipality at a time point ( $t$ ) is impacted by the spatially weighted HR of neighbouring municipalities at a previous time point ( $t-1$ ). These results are consistent with those of previous



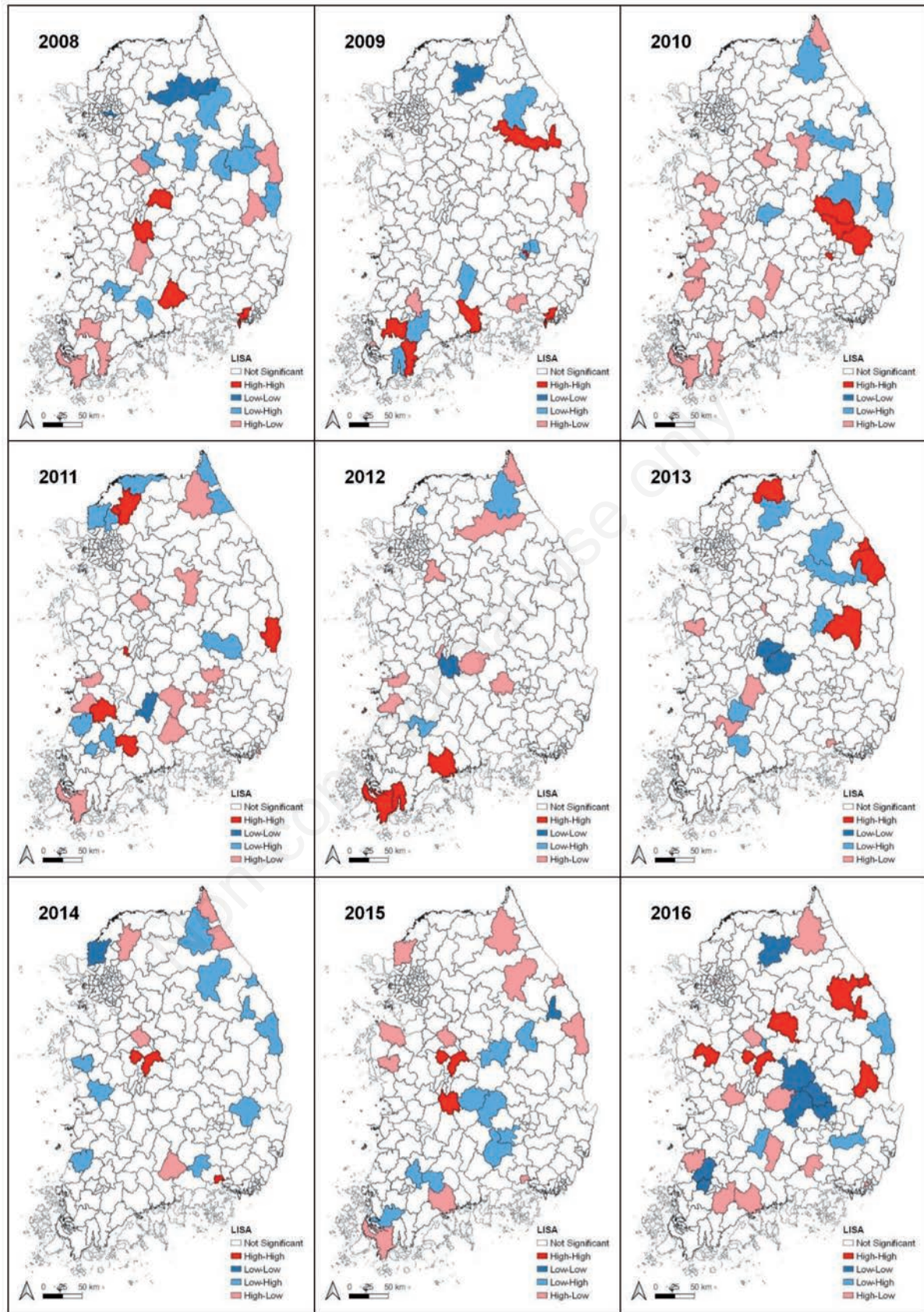


Figure 3. Results of LISA for the homicide rate during the study period.



studies reporting such autocorrelations within the homicide phenomenon (Ye and Wu, 2011; Ruther, 2013). However, it was also shown that temporal dependency is only valid when combined with the spatial dependency of neighbours, resulting in a spill-over phenomena at a later time (time lag). These results indicate that the homicide phenomenon in South Korea spreads to neighbouring municipalities and consistently persists, which reflects underlying social structures. Specifically, this study found that, among several indicators of social disorganization, divorce rate, ethnic heterogeneity, unemployment rate and the number of males in the neighbourhood have a relatively consistent impact on HR. As noted by previous researchers (Sampson and Groves, 1997; Sampson *et al.*, 1997), these variables are to a large degree unpredictable but assumed to disrupt social relationships and discourage people from engaging in organizational action to exert social control over deviant behaviours.

One interesting finding in this study was that the effects of ethnic heterogeneity were not consistent with the traditional assumption of the social disorganization theory that posits that a high level of ethnic heterogeneity hampers social solidarity because the heterogeneity creates language and cultural barriers. However, recent studies have found that ‘immigration may stabilize communities and reduce violence by providing protective community resources and strengthening social institutions and social capital networks’ within ethnic groups (Feldmeyer, 2009 - p. 781). In South Korea, the number of immigrants has consistently increased since the 1990s due to international marriage and the influx of foreign workers (Kong *et al.*, 2010). As such, the ethnic background of the population has diversified, creating language and cultural obstacles that complicate assimilation into the Korean society. However, as some scholars have maintained (Feldmeyer, 2009), immigrants are now highly-motivated to achieve economic success and are dedicated to their multicultural families; therefore, ethnic diversity might now have a negative impact on HR.

### Strengths and limitations

This study has broadened the investigation of the homicide phenomenon by explored the spatial and temporal aspects of homicide in Korea using the spatial panel data model, which has rarely been applied to the study of homicide. The results are supportive for to the development of diverse crime prevention policies at the municipal level. In particular, given that the homicide phenomenon is spatially clustered and temporally consistent at the local level, national policymakers need to disproportionately allocate available resources depending on the level of HR at the municipal level. Also, considering that HR is associated with social disorganization, municipalities with a high level of HR should allocate available resources to reinforce social capital and increase the level of formal or informal social control within municipalities. A heightened level of collective efficacy can promote the community’s capabilities to effectively monitor deviant behaviour (Mancik *et al.*, 2018).

Despite its findings and consequent policy implications, this study has some limitations. Although the spatial panel data model has some advantageous qualities, it assumes that unmeasured heterogeneity between municipalities is time-invariant (Ruther, 2013; Belotti *et al.*, 2016). Over the ten-year study period, unobserved structural characteristics that might have significantly changed over time could have also been correlated with HR. Furthermore, the limited number of explanatory variables due to the issue of data availability might have caused some estimation bias. Thus, future

studies need to include more diverse indicators for social disorganization or social control, such as social inequality (Lizzi *et al.*, 2021) and the number of law enforcement officers, which are assumed to affect HR. In addition, there is a risk that HR violates the normality assumption due to its rare occurrence at the municipality-level. Even though this study transforms the observed values to ameliorate the normality issue, the transformation might result in incorrect inferences in the Poisson distribution (Ruther, 2013). Therefore, future research ought to apply a model that can consider both the unusual distribution and the spatial and temporal dynamics inherent in the investigated phenomenon.

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