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Analyzing the dynamics of homicide patterns in Chicago: ESDA and spatial panel approaches

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A B S T R A C T

This paper studies the relationship between homicide rate and socioeconomic factors at community area level in Chicago from 1960 to 1995. Most of prior studies of social disorganization theory are based on cross-sectional spatial regression or longitudinal studies. This research integrates space and time in testing social disorganization theory. First, exploratory spatial data analysis (ESDA) is used to examine dynamic spatial patterns of these indicators. This investigation justifies the estimation of homicide rates across community areas through panel-data models that extend to include spatial lag and spatial error autocorrelation.

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Introduction

Violent death has been among leading public health and social problems in both western societies and developing countries (Cole & Gramajo, 2009). Homicide research has involved numerous disciplines such as criminology/criminal justice, geography, sociology, and public health. For instance, the Homicide Research Working Group was formed in 1991 to promote the interdisciplinary and international studies of this topic among worldwide researchers and policy makers. Over the course of recent decades, applications of multivariate statistical techniques to homicide at various scales have become an important area of quantitative criminological research (Fox & Swatt, 2009; Land, McCall, & Cohen, 1990; Xie, 2010). Especially, social disorganization theorists have modeled the effects of a wide range of structural indicators on homicide rates using different territorial units (Sampson, Morenoff, & Gannon-Rowley, 2002; Wang & Arnold, 2008). Due to the advantage of panel analysis, panel data models have been widely used in testing social disorganization theory (Bursik, 1986; Hipp, Tita, & Greenbaum, 2009; Liska & Bellair, 1995). Meanwhile, incorporation of spatial effects into social disorganization analysis is considered a necessary and promising direction (Kubrin & Weiter, 2003; Ceccato & Oberwittler, 2008). These two approaches, however, are largely separated from each other, with the former focusing on time and the latter emphasizing space. To date most of panel data models applied in empirical homicide studies still ignore spatial interaction effects.

Spatial analysis is statistically important because it can enhance the inference accuracy, and at the same time reduces estimate bias by considering spatial proximity and dependence (Baller, Anselin, Messener, Deane, & Hawkins, 2001; Heraux, 2007). Spatial analysis is also theoretically and substantively important for detecting not only difference of predictor effect in varying geographic areas, but also the diffusion process of criminal violence (Cohen & Tita, 1999; Cork, 1999; Holinger, Offer, & Ostrov, 1987; Messner et al., 1999). More recently, homicide studies integrating spatial pattern and causality analysis are mushrooming within empirical social disorganization studies (Baller et al., 2001; Nielsen, Lee, & Martinez, 2005). While spatial analysis can generate in-depth visualization and summary of complex spatial patterns, they largely ignore temporal effects. The temporal dynamics of spatial patterns over time has recently gained substantial attention among both the research and practitioner communities in criminology, because of the increasing availability of spatial and temporal datasets. Spatial panel regression offers researchers extended modeling possibilities as compared to the cross-sectional setting for spatial data (Elhorst, 2003, 2009).

This paper aims to examining the space–time relationship between structural covariates and homicide rates in Chicago from both exploratory and confirmatory perspectives. More specifically, this research first explains important concepts and theoretical advances relevant to structural indicators, spatial analysis, and the importance of using community area as a unit of analysis. Second,

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exploratory spatial data analysis (ESDA) is applied to visualize spatial patterns and identify hot spots of homicide rates and structural indicators over years, which explores the homicide phenomenon from an exploratory perspective. Third, spatial panel regression is conducted, and the results are reported and explained, which examines the homicide phenomenon from the confirmatory perspective.

Table 1
Global Moran's I of homicide rate and three structural indicators (significant level: * < 0.05, ** < 0.01).

	1965	1970	1980	1990
poor	0.5513**	0.5619**	0.5747**	0.5230**
difhou	0.1574*	0.3980*	0.4779**	0.5789**
foreig	0.5363**	0.4780**	0.5067**	0.5290**
hr	0.5408**	0.5332**	0.6750**	0.5019**

Literature review

Social disorganization theory

Social disorganization refers to the inability of a community to accomplish the common value of its residents in order to sustain effective social controls (Kornhauser, 1978). Following Burgess' urban theory, Shaw and McKay (1942) develop the social disorganization perspective in studying Chicago neighborhoods. They find that areas with high delinquency rate are often characterized by poverty, population heterogeneity, and high population turnover. According to them, poverty impedes slum people's survival needs, residential mobility blocks familiarity among residents, and heterogeneity confuses juveniles of different values. In other words, these structural factors break down the organic social control within communities, which lead to the higher level of delinquency.

Contemporary social disorganization theorists somehow redirect their concentration to the mechanism or process of informal social control in neighborhoods (Bursik & Grasmick, 1993; Morenoff, Sampson, & Raudenbush, 2001). Even controlling for informal social control, neighborhood structural indicators still significantly decide neighborhood crime or victimization level (Burchfield, 2009; Sampson, Raudenbush, & Earls, 1997). Three factors are considered as crucial structural determinants of crime: low socioeconomic status, residential mobility, and ethnic heterogeneity (Kornhauser, 1978; Sampson et al., 1997; Schreck, McGloin, & Kirk, 2009).

In terms of low socioeconomic status (SES) or concentrated disadvantage, socioeconomic hardship impedes social organization because low-SES communities have a weaker organizational base. Such communities lack the financial and human capital resources to identify and protect community interests and to provide activities for teenagers (Sampson & Groves, 1989; Vélez, 2009). Moreover, low-SES communities may lack the capacity to solicit extra-neighborhood resources, including public service and control (Bursik & Grasmick, 1993). Residential stability promotes social organization, because the stability is vital for the formation and maintenance of both formal and informal social networks among community members. In addition, residential mobility weakens social relations among community members, and disrupts the ability to maintain an organized community through informal social control. Communities with high levels of residential stability tend to have higher level of interconnection among community members, while population turnover might make interpersonal relationships in communities difficult to establish (Crutchfield, Geerken, & Gove et al., 1982; Irwin, Tolbert, & Lyson, 1999; Xie & Mcdowall, 2008). Empirical study shows that the stability of the population in a neighborhood is negatively correlated with crime (Ackerman, 1998; Harries, 1974; Parente & Mahoney, 2009). Ethnic heterogeneity is predicted to prevent the ability of community residents from achieving consensus (Sampson & Groves, 1989). A high level of ethnic heterogeneity (lack of ethnic residential concentration) tends to weaken the control of local youths because residents might lack communication and interaction (Sun, Triplett, & Gainey, 2004). Due to disruptive community organization, a community characterized by ethnic heterogeneity is usually criminogenic (Herzog, 2009).

In recent years, with a growing recognition of the importance of space to many socioeconomic processes (Goodchild, Anselin, Appelbaum, & Harthorn, 2000), spatial crime analysis is gradually returning to the forefront of criminological inquiry. As a space-based theory of crime, social disorganization theory has served an substantive motivation to contribute to this transformation. In addition, more advanced analytical tools put space in the central role on crime analysis (Grubesic & Mack, 2008; Messner et al., 1999; Roncek & Maier, 1991). Spatial crime analysis has witnessed the trends of combining spatial visualization and spatial data analysis techniques, as well as a substantial body of empirical studies. Under the framework of exploratory data analysis (EDA) (Tukey, 1977), exploratory spatial data analysis (ESDA) is a set of methods aiming at describing and visualizing geographical distributions, to detect atypical localizations or spatial outliers, to identify patterns of spatial association, and to indicate forms of spatial heterogeneity (Grubesic & Mack, 2008; Haining, 1990). These methods provide measures of global and local spatial autocorrelation, which show what the distribution of a set of numbers looks like when expressed graphically. Spatial autocorrelation has been estimated in the regression in empirical analysis of social disorganization theory using various aggregated units (Barnett & Mencken, 2002; Lee, Maume, & Ousey, 2003; McCall & Nieuwbeerta, 2007), especially

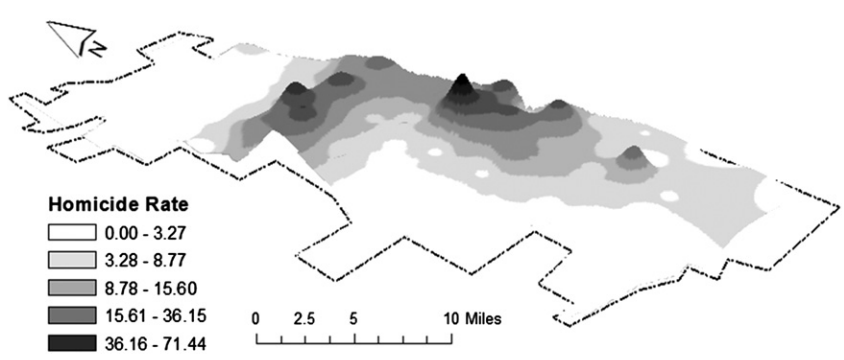

Fig. 1. Homicide rate surface in 1965 (Homicide rate in a community area is calculated by dividing homicide counts to population in that community area then multiplying 1,00,000).

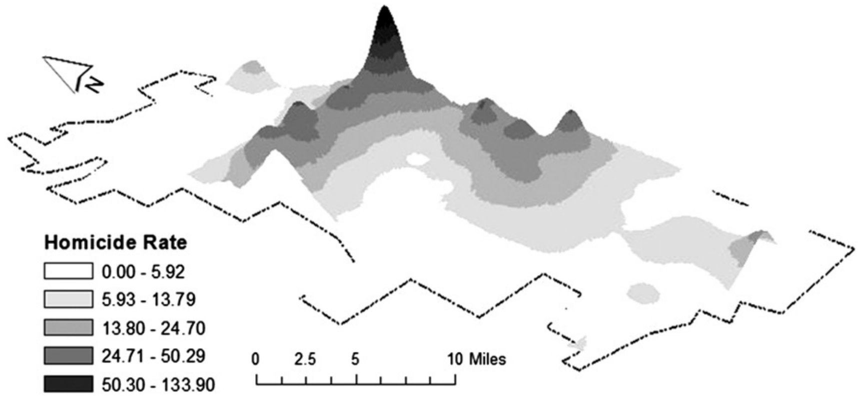

Fig. 2. Homicide rate surface in 1970.

finer aggregated units, such as census tract (Anderson, 2006; Morenoff & Sampson, 1997; Sun et al., 2004).

Chicago community area as unit of analysis

According to 2000 census, Chicago was the third largest city in the United States, with a diverse population of almost 3 million (Dell, Whitman, Shah, Silva, & Ansell, 2005). Chicago was officially divided into 77 community areas by the Social Science Research Committee at the University of Chicago in 1920s. These sociologists who devised the community areas attempted to create socially homogenous regions or neighborhood-like districts. Boundaries of these communities were drawn around existing neighborhoods and landmarks such as rivers and railroad tracks. Chicago Community Area designations are considered to be very durable.

Since 1943, Chicago community areas have been studied by researchers in the fields of sociology, geography, criminal justice, and urban planning; by city managers for allocations of funds and services; and by citizens interested in relocating to or starting a business in a particular area (Bremner et al., 1996). Especially in health and epidemiology study, Chicago community areas often serve as loci for gathering and analyzing health data, delivering health service, and implementing community-based interventions. Reinhard, Paul, and McArley (1997) study the pediatric tuberculosis problem in Chicago's 77 community areas. Comparison of case rates with socioeconomic and health indicators show the highest rates in communities with multiple indicators of poverty, including overcrowded housing units, low median income, and high infant mortality rates. Based on their findings, they urge more resources to be provided to the community areas with the highest incidence rates. Shaw, Whitman, and Silva (2006) notice that the community areas assessed are homogenous, lending valuable information to assessments of racial and ethnic health disparities. In addition, effective community-based initiatives are designed to improve the residents' health. Similarly, some studies examine community area-level variations in smoking behavior (Dell, et al., 2005). Youm, Mackesy-Amiti, Williams, and Ouellet (2009) extend the analysis of sexual network linkages beyond individual and risk group levels to a community area level in Chicago.

Data

Two datasets are utilized in the present study: a socio-demographic dataset and a homicide count dataset. Annual homicide count data are retrieved from murder analysis files of the Chicago Police Department from 1965 to 1995 (Block, Block & the Illinois Criminal Justice Information Authority, 1998). The corresponding four-wave community area level socio-demographic data are from the Community Area Fact Books.

Community area is used as the unit of analysis, and 75 community areas in Chicago city are included in this study. As the historically formed regions, community areas have remained unchanged since their inception, except for the addition of O'Hare and the splitting of Edgewater from Uptown. Hence, we only use the 75 unchanged community areas in the analysis by excluding the above two areas. Another reason for excluding O'Hare, an airport area, is due to the land use function and the lack of geographic continuity. The compiled dataset includes some community area-level structural indicators for the four decennial years and 31 years' homicide data in these 75 community areas.

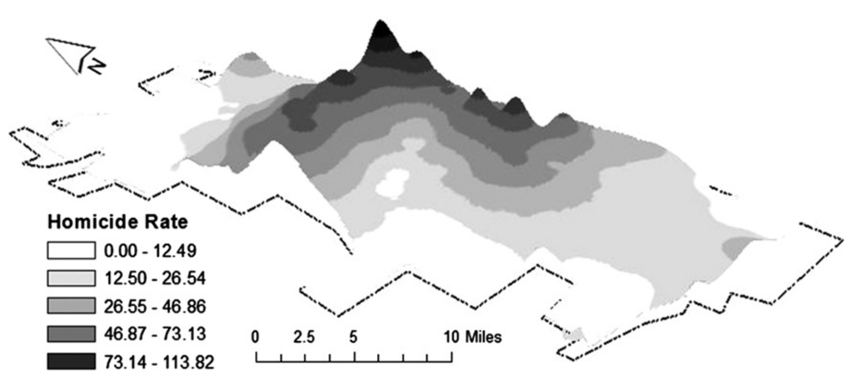

Fig. 3. Homicide rate surface in 1980.

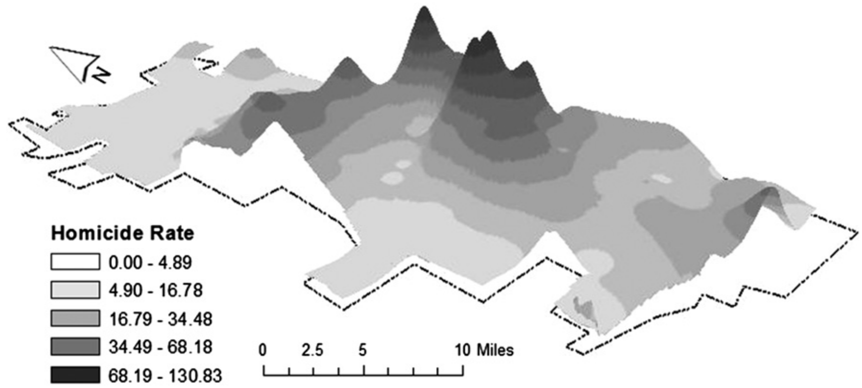

Fig. 4. Homicide rate surface in 1990.

The independent variables are three metric-scaled socio-demographic variables, including *percentage of people below poverty line* (poor), *percent of people staying in the same house as in 5 years ago* (difhou), and *percent of foreign-born people* (foreig). In social disorganization studies, these variables can be used as the proxies of three dimensions of community structure respectively, including concentrated disadvantage, residential stability, and immigrant concentration. To satisfy the basic statistical assumptions of multivariate regression analysis, *percentage of people below poverty line* is logged for the regression analysis. All three independent variables are in six time points (1965, 1970, 1975, 1980, 1985, and 1990), where the values in non-decennial years are estimated by the corresponding values in the nearby two decennial years.

The dependent variable is the *homicide rate* (hr) of each community area at aforementioned six time points. Homicide rate in a community area is calculated by dividing homicide counts to population in that community area then multiplying 1,00,000. To avoid extreme heterogeneity, the rates are smoothed by taking a three-year average of the community area homicide count centered on each six time points. These averages are divided by the single-year community area population figures in a census year. Homicide rate is selected as the dependent variable because it is an accurate indicator of community violence and a generalized predictor of general community well-being. Compared with homicide count, homicide rate is a better indicator of relative risk within community areas, especially considering that homicide has a serious and direct impact on the perceived livability of a community. Due to the scarcity of homicide incidents, the original values of averaged homicide rate will take a logarithmic transformation (the value of 1 is added to the rates to avoid the missing data) (Wang, 2005).

Exploratory spatial data analysis

Recent years have witnessed significant interest in exploratory spatial data analysis (ESDA) techniques in crime analysis (Grubesic & Mack, 2008). ESDA should be considered as a descriptive step before suggesting dynamic factors to explain the spatial patterns under study and before estimating and testing more sophisticated

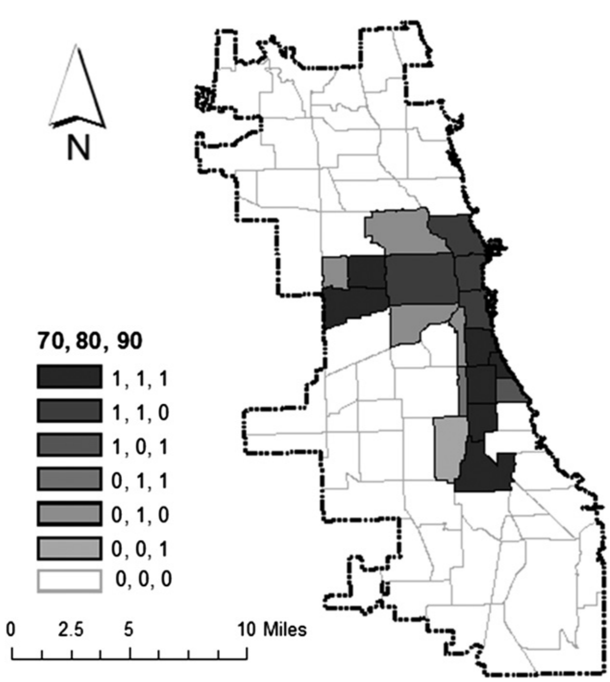

Fig. 5. Temporal hot spots of homicide rate (1970, 1980, 1990)

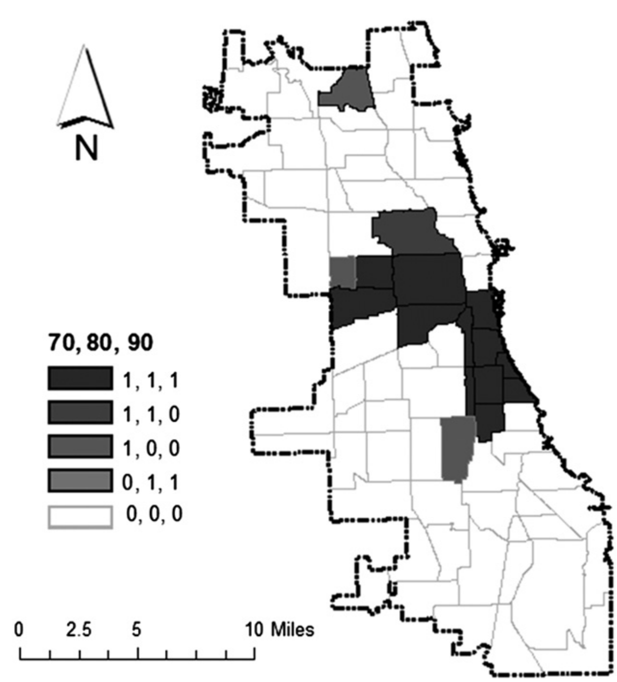

Fig. 6. Temporal hot spots of poor (1970, 1980, 1990)

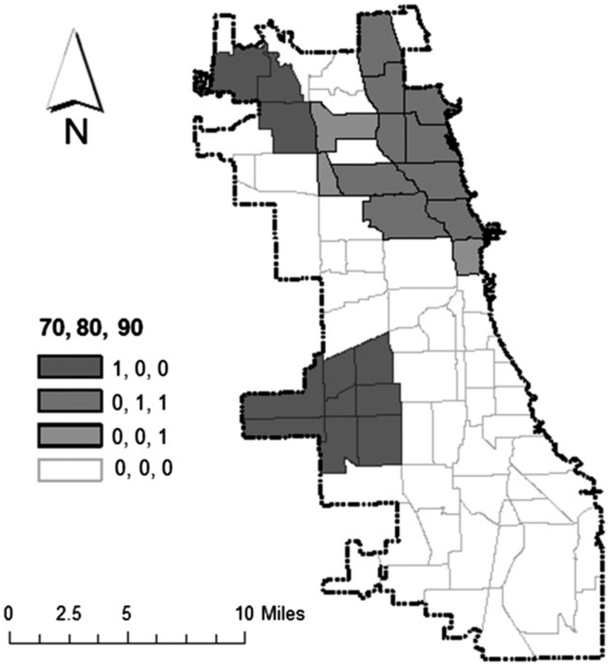

Fig. 7. . Temporal hot spots of difhou (1970, 1980, 1990).

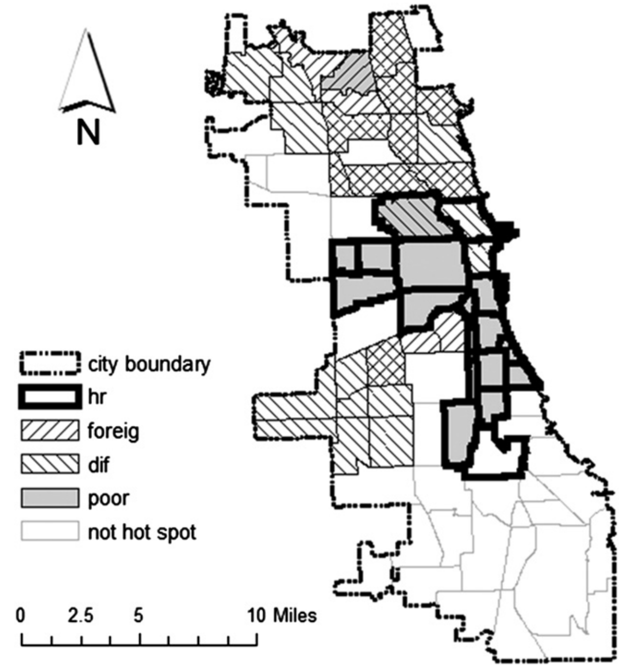

Fig. 9. Comprehensive hot spots (1970, 1980, 1990)

regression models (Anselin, 2005). ESDA can reveal complex spatial phenomenon not identified otherwise, and it forms the basis for formulating novel research questions. The development of new methods of ESDA has stimulated a number of research efforts (Goodchild, 2006; Rey & Ye, 2010).

Global autocorrelation is assessed by global Moran's I statistic. A positive and significant Moran's I value indicates a general pattern of clustering in space of similar values (Anselin, 1995). Independent and dependent variables in four time points (1965, 1970, 1980, and 1990) will be used in the global and local autocorrelation analysis.

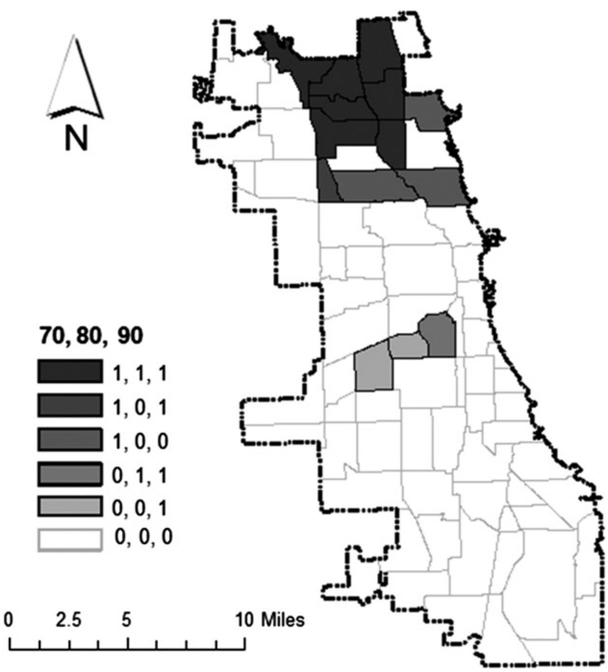

Fig. 8. Temporal hot spots of foreig (1970, 1980, 1990).

Table 1 depicts the general trend of global spatial dependence level over time. All the indicators suggest the stability of spatial clustering level over time, except a growing global spatial autocorrelation of mobility (difhou). However, a series of similar global spatial clustering level might mask a dramatic spatial restructuring (Rey & Ye, 2010). Figs. 1–4 interpolate and visualize homicide rates at the community area level, thus creating homicide rate surfaces over time. From 1965 to 1990, the peaks of homicide rates dramatically developed around the city loop and spread towards the other parts of the city.

Compared with the global indicator, local indicator spatial autocorrelation (LISA) considers spatial proximity for each community area, which can help to identify the hot spots of structural factors and homicide rates (Anselin, 1995). Anselin's LISA

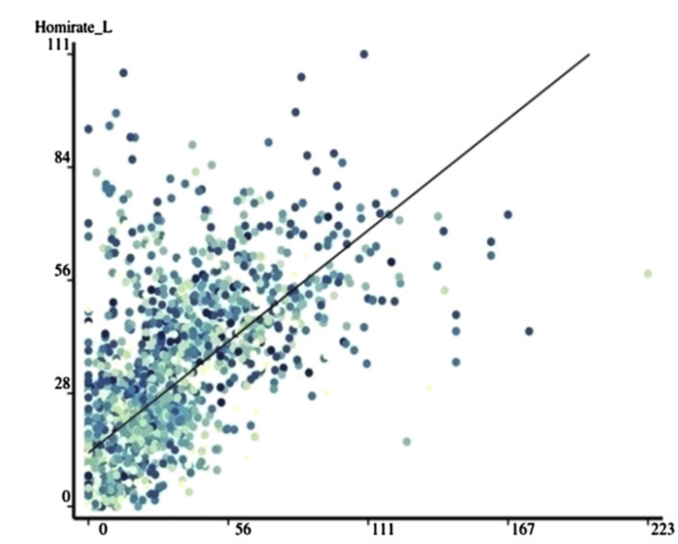

Fig. 10. Conditional scatter plot of hmocide rate.

is used here to identify significant local spatial clusters of the selected indicators, as well as analyze local spatial instability and spatial regimes. A LISA significance map can be generated at each year showing the community areas with significant LISA values and influential observations (hot spots) can thus be identified on the map. We suggest a temporal stability mapping of hot spots by overlaying hot spots in 1970, 1980, and 1990 for homicide rates and the three independent variables, which extends Anselin's LISA significance map into a temporal context (Figs. 5–8). For example, six categories of temporal hot spot stability are identified in Fig. 5. If a community area remains the hot spot of homicide rate in all three years (1970, 1980, 1990), it is identified as "1, 1, 1". A community is labeled as "1, 0, 1", if it is the hot spot except 1980. Hence, the label of "0, 0, 0" suggests that the corresponding region has never been a hot spot in these years. 18 community areas have been the homicide rate hot spot of six categories, and *percentage of people below poverty line* (poor) hot spot is reported to have 16 community areas with four types. Regarding the hot spot of *percent of people staying in the same house as in 5 years ago* (difhou), 23 regions are identified with three types of temporal stability, while 14 communities have been the *percent of foreign-born people* (foreig) hot spot under five categories.

Fig. 5 (homicide rate) and Fig. 6 (poor) are similar in the spatial extent of hot spots over time while their temporal stabilities demonstrate distinct patterns. Fig. 7 (difhou) and Fig. 8 (foreig) show more segregated patterns. Fig. 9 illustrates the temporal hot spots of four variables on one map. Two phenomena warrant notice in this comprehensive figure: first, the hot spots of homicide rates rarely overlap those of different house percentages and foreign born percentages; second, Southern Chicago has a significant size of community areas which have not been any hot spot over years.

In addition to gaining an understanding of the role of spatial dependence in the analysis of spatial patterns, we are also interested in the consistency of these effects over time (Rey & Ye, 2010). The conditioned scatter plot provides us an overall picture of the change of the homicide rates over time (conditioned on years) with the spatial proximity taken into account (Rey & Janikas, 2006). Fig. 10 contains 2250 points (75 communities over 30 years). The color of points represents the corresponding year. A lighter color represents data in earlier years, while darker colors represent those in more recent years. For each point, the x-axis corresponds to the focal community's homicide rate and y-axis corresponds to its spatial lag. The spatial lag is computed using the average of the focal community's neighbors' homicide rates. In other words, the consideration of spatial lag introduces the spatial proximity into the analysis, which is crucial for computing spatial autocorrelation tests and specifying spatial regression models (Anselin, 2005). It appears that most of the lighter points concentrate in the lower left section, while the darker dots scatter and locate in the upper part. This map indicates that the homicide risk rises over time at the community area level, along with the emergence of more diverse patterns, which further explains Figs. 1–4.

All the above exploratory spatial analysis outputs suggest the existence of spatial interaction effects among community area-level homicide rates and the structural indicators. To explore their relationship, a diagnostics is carried out to check the existence of spatial patterns (Anselin, 2005). Table 2 shows the diagnostics results for the cross-sectional regression model at each year (1965, 1970, 1975, 1980, 1985, and 1990). First, only the Moran's I of residuals in 1965 indicates the existence of spatial autocorrelation among the errors (the statistical significant level of 0.05). It suggests the need to choose a spatial regression model for the year of 1965, which is either spatial lag or spatial error model. At any other fivetime points, there is no need for carrying out spatial regression, because the residuals are not spatially auto-correlated at the statistical significant level. However, this is at odds with the observed strong spatial interaction patterns illustrated by ESDA methods in the earlier part of this section. Second, all the adjusted R squares are relatively large, indicating that the three selected independent variables can explain a significant part of the homicide rate's variation[1]. However, the magnitude and the trend of these independent variables vary a lot across all the years. For example, four years out of six years report that either difhou or foreig is not statistically significant. In addition, difhou is a positive contributor to homicide rate since 1980 while it is negatively related before 1975. It is not clear whether a conclusion can be made regarding such a shift of relationship. Moreover, the explanatory power of lgpoor gradually decreases. All the above results show that some types of complicated spatial interaction might exist, as shown by considerable variability in both estimated coefficients and statistical significance levels for all these indicators over time (Table 2). Neither OLS nor spatial regression models can fully address the relationship between the homicide rate and its explanatory variables. Hence, this relationship needs to be further examined using a spatial panel regression approach, which is expected to generate a series of consistent results.

Spatial panel regression

Generally speaking, the fixed effect model is favored when the regression analysis is applied to a precise set of regions; random effect, instead, is an appropriate specification if a certain number of individuals are randomly drawn from a large population of reference (Baltagi, 2001). For this reason, since our data set consists on the observations of the same 75 communities, we estimate a fixed effect panel data model. At the same time, we test the fixed effects specification against the random effects specification of panel data models. These models are extended to include spatial error autocorrelation or a spatially lagged dependent variable using Hausman's specification test. And it also suggests that the fixed effects model is a better option. Hence, the aim of this section is to estimate a fixed effect panel data model extended to account for spatial lag and spatial error autocorrelation (Elhorst, 2003, 2009).

When specifying spatial interaction among communities, a model contains a spatially lagged dependent variable or a spatial autoregressive process in the error term, known as the spatial lag or the spatial error model, respectively. Spatial lag indicates a possible diffusion process while spatial error model focuses on the unexplained residuals by structural factors (Lacombe & Shaughnessy, 2004). Hence, the spatial lag model posits that homicide rate depends on the homicide rate observed in neighboring units and on a set of observed three local independent variables. In the empirical literature on crime interaction among local communities, the spatial lag model is theoretically consistent with the situation where homicide rate in focal community is jointly determined with that of the neighboring communities (Anselin, 2005).

The spatial lag model's equation is given as:

$$y_{it} = \delta \sum w_{ij} y_{it} + x_{it}\beta + \mu_i + \varepsilon_{it}$$

where i is an index of the cross-sectional dimension (spatial units), with i = 1, …, N. 75 communities serve as the cross-sectional spatial units. The index of t represents the temporal periods, with t = 1, …, T. The six years are considered as the six time points in the temporal

[1] In criminology/criminal justice research, R-squared values of regressions about social behavior/personal choice are usually low. The reason to have a relatively high R-squared values here is that this research uses the aggregate data at the community level, which makes the homicide rate more predictable. In other words, the fraction of variance is much better explained by the models used in this paper.

Table 2
OLS regression of homicide rates and Moran's I of residuals in Chicago community areas, 1965-1990 (* < 0.05, ** < 0.01).

	1965	1970	1975	1980	1985	1990
lgpoor	1.282**	0.988**	1.072**	0.962**	0.868**	0.871**
difhou	−0.007	−0.017**	−0.019*	0.006*	0.007*	0.002
foreig	−0.008*	−0.018**	−0.003	−0.005	−0.011**	−0.011**
Constant	0.146	1.218**	1.039**	0.038	0.119	0.401**
Moran's I (error)	2.111*	1.119	0.326	0.448	0.489	−0.108
Adjust R^2	0.714	0.773	0.795	0.794	0.784	0.776
N	75	75	75	75	75	75

dimension (1965, 1970, 1975, 1980, 1985, 1990). δ is called the spatial autoregressive coefficient; w_{ij} is an element of a spatial weights matrix W; W describes the spatial arrangement of all the spatial units in the sample; y_{it} is an observation on the dependent variable (homicide rate) at i and t; x_{it} is an (1,K) row vector of observed characteristics of spatial unit i at time t; β is a matching (K,1) vector of fixed but unknown parameters; ε_{it} is an independently and identically distributed error term for i and t with zero mean and variance σ^2, which represents unobserved factors for observation i at time t; μ_i denotes a spatial specific effect. The standard reasoning behind spatial specific effects is that they control for all space-specific time-invariant variables whose omission could bias the estimates in a typical cross-sectional study.

The spatial error model, on the other hand, argues that the dependent variable depends on a set of observed local indicators and that the error terms are spatially auto-correlated. The equation is given as:

$$\varphi_{it} = \rho \sum w_{ij}\, \varphi_{it} + \varepsilon it$$

$$y_{it} = x_{it}ß + \mu_i + \varphi_{it}$$

where φ_{it} reflects the spatially auto-correlated error term and ρ is called the spatial autocorrelation coefficient (Elhorst, 2003, 2009). In the empirical literature on crime interaction among local communities, the spatial error model is consistent with a situation where determinants of homicide rate omitted from the model are correlated over space, and with a situation where unobserved factors follow a spatial pattern (Anselin, 2005).

Spatial panel models with spatial fixed effects have large R square in both spatial lag and spatial error panel models (Table 3 and Table 4). Both of the two spatial panel regressions suggest that difhou and foreign are significantly negative while lgpoor is significantly positive related to homicide rate. These signs of coefficients are consistent with Sampson et al. (1997)'s findings. The results indicate that neighborhood characteristics based on social disorganization theory are important in explaining the variability in homicide rate trajectories. In particular, spatial error autocorrelation model appears to be a more reasonable solution, because the coefficient of spatial lag is not significant at the 0.05 level. The main advantages deriving from this result are in the fact that we can take into account the spatial dependence in the data set, specifying spatial interaction types (spatial lag or spatial error), and get more reliable estimates of the coefficients (Elhorst, 2003, 2009).

Table 3
Fixed effect with spatial lag autocorrelation.

Dependent variable		lghr	
R-squared		0.865	
Log-Likelihood		81.375	
Number of Observations		450	
Number of Variables		3	
Variable	Coefficient	t-stat	Probability
lgpoor	0.561	7.147	0.000
difhou	−0.005	−4.985	0.000
foreign	−0.012	−6.682	0.000
Spatially lagged lghr	0.104	1.718	0.086

Table 4
Fixed effect with spatial error autocorrelation.

Dependent variable		lghr	
R-squared		0.869	
Log-Likelihood		84.862	
Number of Observations		450	
Number of Variables		3	
Variable	Coefficient	t-stat	Probability
lgpoor	0.612	7.300	0.000
difhou	−0.005	−4.267	0.000
foreign	−0.013	−6.263	0.000
Spatial autocorrelation coefficient	0.281	4.804	0.000

Summary and discussion

This paper yields several noteworthy findings. The importance of neighborhoods in understanding homicide has been widely noted in law enforcement agencies. Both homicide incidents and neighborhood characteristics are not evenly distributed over space and time. However, most studies only analyze the cross-sectional relationship and fail to account for temporal dynamics. This paper adds to existing research by empirically studying both the spatial and temporal aspects of homicide patterns at the community area level. First, ESDA reveals possible complicated spatial interaction among homicide rates and community characteristics over years. Various types of hot spots are identified over time. OLS and spatial regression model choice diagnostics indicate that these two cross-sectional regression methods cannot generate consistent findings for all the time points. Hence, spatial panel regression is considered a solution.

Accordingly, by incorporating spatial dependence into fixed effects panel regression model, the overall predicting ability for homicide rate at the community area level has been improved, and at the same time the estimation of three independent variables becomes consistent. An increase in percent of people staying in the same house as in 5 years ago (difhou) or percent of foreign-born people (foreig) decreases the level of homicide, while the increase of percentage of people below poverty line (poor) is related with a higher level of homicide. This analysis further indicates the importance of considering spatial effects over time when examining the association between neighborhood characteristics and homicide rate. As Goodchild (2006) states, "while geographers have always been custodians of knowledge about form, arguably the custodians of process have been the substantive sciences of surficial geology, ecology, hydrology, epidemiology, demography, economics, etc. A concern for process is therefore likely to change the landscape of GIScience dramatically, requiring much closer interaction with these sciences". Since crime occurs across space and over time, closer interaction between geography and criminology should lead to a better understanding of the relationship between neighborhoods and crime.

Historically formed neighborhoods are desirable units of analysis in social disorganization research, because their boundaries are relatively stable and less arbitrary, compared to census tracts and patrol beats. In other words, this type of spatial unit is closer to the ideal definition of neighborhood. However, since only 75 community areas and six time points in Chicago are employed in this study due to the data availability, the statistical power of our results might be low. Further studies might use more time points.

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Reference:

Ackerman, W. V. (1998). Socioeconomic correlates of increasing crime rates in smaller communities. *Professional Geographer, 50*, 372–387.
Anderson, M. A. (2006). A spatial analysis of crime in Vancouver, British Columbia: a synthesis of social disorganization and routine activity theory. *The Canadian Geographer, 50*(4), 487–502.
Anselin, L. (1995). Local indicators of spatial association–LISA. *Geographical Analysis, 27*, 93–115.
Anselin, L. (2005). *Exploring spatial data with GeoDa: A workbook*. Center for Spatially Integrated Social Science.
Baller, R. D., Anselin, L., Messener, S. F., Deane, G., & Hawkins, D. F. (2001). Structural covariates of U.S. county homicide rates: incorporating spatial effects. *Criminology, 39*(3), 561–590.
Baltagi, B. H. (2001). *Econometric analysis of panel data*. Chichester, UK: Wiley.
Barnett, C., & Mencken, F. C. (2002). Social disorganization theory and the contextual nature of crime in nonmetropolitan counties. *Rural Sociology, 67*(3), 372–393.
Block, C. R., Block, R. L., & the Illinois Criminal Justice Information Authority. (1998). *Homicides in Chicago, 1965-1995. Computer file, 4th ICPSR version*.
Bremner, D. H., Mitchell, S. R., Staines, H., Reguig, F. B., Kirk, D. L., & Kelly, M. C. (1996). Profiling a city: information resources on Chicago's 77 community areas. *Journal of Government Information, 23*(1), 1–11.
Burchfield. (2009). Attachment as a source of informal social control in urban neighborhoods. *Journal of Criminal Justice, 37*(1), 45–54.
Bursik, R. (1986). Delinquency rates as sources of ecological change. In J. M. Byrne, & R. J. Sampson (Eds.), *The Social Ecology of Crime*. New York: Springer-Verlag.
Bursik, R. J., & Grasmick, H. G. (1993). *Neighborhoods and crime: the dimensions of effective community control*. New York: Lexington Books.
Ceccato, V., & Oberwittler, D. (2008). Comparing spatial patterns of robbery: evidence from a Western and an Eastern European city. *Cities, 25*(4), 185–196.
Cohen, J., & Tita, G. (1999). Diffusion in homicide: exploring a general method for detecting spatial diffusion processes. *Journal of Quantitative Criminology, 15*(4), 451–493.
Cole, J. H., & Gramajo, A. M. (2009). Homicide rates in a cross-section of countries: evidence and interpretations. *Population and Development Review, 35*(4), 749–776.
Cork, D. (1999). Examining space-time interaction in city-level homicide data: crack markets and the diffusion of guns among youth. *Journal of Quantitative Criminology, 15*, 379–406.
Crutchfield, R., Geerken, M., & Gove, W. (1982). Crime rate and social integration. *Criminology, 20*, 467–478.
Dell, J. L., Whitman, S., Shah, A. M., Silva, A., & Ansell, D. (2005). Smoking in 6 diverse Chicago communities – a population study. *American Journal of Public Health, 95*, 1036–1042.
Elhorst, J. P. (2003). Specification and estimation of spatial panel data models. *International Regional Science Review, 26*(3), 244–268.
Elhorst, J. P. (2009). Spatial panel data models. Ch. C.2. In M. M. Fischer, & A. Getis (Eds.), *Handbook of Applied Spatial Analysis*. Berlin/Heidelberg/New York: Springer.
Fox, J. A., & Swatt, L. (2009). Multiple imputation of the supplementary homicide reports, 1976–2005. *Journal of Quantitative Criminology, 25*(1), 51–77.
Goodchild, M. (2006). Geographical information science: fifteen years later. In P. Fisher (Ed.), *Classics from IJGIS: Twenty years of the International Journal of Geographical Information Science and Systems, Vol. 2* (pp. 107–133). Boca Raton: CRC Press.
Goodchild, M. F., Anselin, L., Appelbaum, R. P., & Harthorn, B. H. (2000). Toward spatially integrated social science. *International Region Science Review, 23*(2), 139–159.
Grubesic, T., & Mack, E. (2008). Spatio-temporal interaction of urban crime. *Journal of Quantitative Criminology, 24*(3), 285–306.
Haining, R. F. (1990). *Spatial data analysis in the social and environmental sciences*. Cambridge: Cambridge University Press.
Harries, K. D. (1974). *The geography of crime and justice*. New York: McGraw-Hill.
Heraux. (2007). Spatial data analysis of crime. *Social Science Computer Review, 25*(2), 259–264.
Herzog, S. (2009). Ethnic and immigrant residential concentration, and crime rates. *Journal of Criminal Justice, 37*(5), 427–434.
Hipp, J. R., Tita, G. E., & Greenbaum, R. F. (2009). Drive-bys and trade-ups: examining the directionality of the crime and residential instability relationship. *Social Forces, 87*(4), 1777–1812.
Holinger, P. C., Offer, D., & Ostrov, E. (1987). Suicide and homicide in the United States: an epidemiologic study of violent death, population changes, and the potential for prediction. *American Journal of Psychiatry, 144*, 215–219.
Irwin, M., Tolbert, C., & Lyson, T. (1999). There's no place like home: nonmigration and civic engagement. *Environment and Planning A, 31*(12), 2223–2238.
Kornhauser, R. (1978). *Social sources of delinquency: An appraisal of analytic models*. Chicago: University of Chicago Press.
Kubrin, C. E., & Weiter, R. (2003). New direction in social disorganization theory. *Journal of Research in Crime and Delinquency, 40*(4), 374–402.
Lacombe, D., & Shaughnessy, T. M. (2004). Accounting for spatial error correlation in the 2004 presidential popular vote. *Public Finance Review, 35*(4), 480–499.
Land, K. C., McCall, P. L., & Cohen, L. E. (1990). Structural covariates of homicide rates: are there any invariance across time and social space. *American Journal of Sociology, 95*(4), 922–963.
Lee, M. R., Maume, M. O., & Ousey, G. C. (2003). Social isolation and lethal violence across the metro/nonmetro divide: the effects of socioeconomic disadvantage and poverty concentration on homicide. *Rural Sociology, 68*(1), 107–131.
Liska, A., & Bellair, P. (1995). Violent-crime rates and racial composition. *American Journal of Sociology, 101*, 578–611.
McCall, P. L., & Nieuwbeerta, P. (2007). Structural covariates of homicide rates: a European city cross-national comparative analysis. *Homicide Studies, 11*, 167–188.
Messner, S. F., Anselin, L., Baller, R. D., Hawkins, D. F., Deane, G., & Tolnay, S. E. (1999). The spatial patterning of county homicide rates: an application of exploratory spatial data analysis. *Journal of Quantitative Criminology, 15*, 423–450.
Morenoff, J. D., & Sampson, R. J. (1997). Violent crime and the spatial dynamics of neighborhood transition: Chicago, 1970–1990. *Social Forces, 76*(1), 31–64.
Morenoff, J. D., Sampson, R. J., & Raudenbush, S. W. (2001). Neighborhood inequality, collective efficacy, and spatial dynamics of urban violence. *Criminology, 39*(3), 517–559.
Nielsen, A. L., Lee, M. T., & Martinez, J. R. (2005). Integrating race, place and motive in social disorganization theory: lessons from a comparison of black and latino homicide types in two immigrant destination cities. *Criminology, 43*(3), 837–872.
Parente, M. E., & Mahoney, J. L. (2009). Residential mobility and exposure to neighborhood crime: risks for young children's aggression. *Journal of Community Psychology, 37*(5).
Reinhard, C., Paul, W., & McArley, J. (1997). Epidemiology of pediatric tuberculosis in Chicago, 1974 to 1994: a continuing public health problem. *American Journal of the Medical Sciences, 313*(6), 336–340.
Rey, S. J., & Janikas, M. V. (2006). STARS: space–time analysis of regional systems. *Geographical Analysis, 38*(1), 67–86.
Rey, S., & Ye, X. (2010). Comparative spatial dynamics of regional systems. In Páez., J. Le Gallo, R. Buliung, & S. Dall'Erba (Eds.), *Progress in Spatial Analysis:Theory, Computation, and Thematic Applications*. Springer.
Roncek, D. W., & Maier, P. A. (1991). Bars, blocks, and crimes revisited: linking the theory of routine activities to the empiricism of hot spots. *Criminology, 29*, 725–755.
Sampson, R. J., & Groves, W. B. (1989). Community structure and crime: testing social- disorganization theory. *American Journal of Sociology, , 94*(4), 774–802.
Sampson, R. J., Morenoff, J. D., & Gannon-Rowley, T. (2002). Assessing "neighborhood effects": social process and new directions in research. *Annual Review of Sociology, 28*, 443–478.
Sampson, R. J., Raudenbush, S. W., & Earls, F. (1997). Neighborhoods and violent crime: a multilevel study of collective efficacy. *Science, 277*, 918–924.
Schreck, C. J., McGloin, J. M., & Kirk, D. S. (2009). On the origins of the violent neighborhood: a study of the nature and predictors of crime-type differentiation across Chicago neighborhoods. *Justice Quarterly, 26*(4), 771–794.
Shaw, A. M., Whitman, S., & Silva, A. (2006). Variations in the health conditions of Chicago community areas: a case for local-level data. *American Journal of Public Health, 96*(8), 1485–1491.
Shaw, C. R., & McKay, H. D. (1942). *Juvenile delinquency and urban areas*. Chicago: University of Chicago Press.
Sun, I. V., Triplett, R., & Gainey, R. R. (2004). Neighborhood characteristics and crime: test of Sampson and Groves' model of social disorganization. *Western Criminology Review, 5*(1), 1–16.
Tukey, J. W. (1977). *Exploratory data analysis*. Addison-Wesley.
Vélez, M. B. (2009). Contextualizing the immigration and crime effect an analysis of homicide in Chicago neighborhoods. *Homicide Studies, 13*(3), 325–335.
Wang, F. (2005). Job access and homicide patterns in Chicago: an analysis at multiple geographic levels based on scale-space theory. *Journal of Quantitative Criminology, 21*(2), 195–217.
Wang, F., & Arnold, M. T. (2008). Localized income inequality, concentrated disadvantage and homicide. *Applied Geography, 28*(4), 259–270.
Xie, M. (2010). The effects of multiple dimensions of residential segregation on Black and Hispanic homicide victimization. *Journal of Quantitative Criminology, 23*(6), 237–268.
Xie, M., & Mcdowall, D. (2008). The effects of residential turnover on household victimization. *Criminology, 46*(3), 539–575.
Youm, Y., Mackesy-Amiti, M., Williams, C., & Ouellet, L. (2009). Identifying hidden sexual bridging communities in Chicago. *Journal of Urban Health, 86*(s1), 107–120.