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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.

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

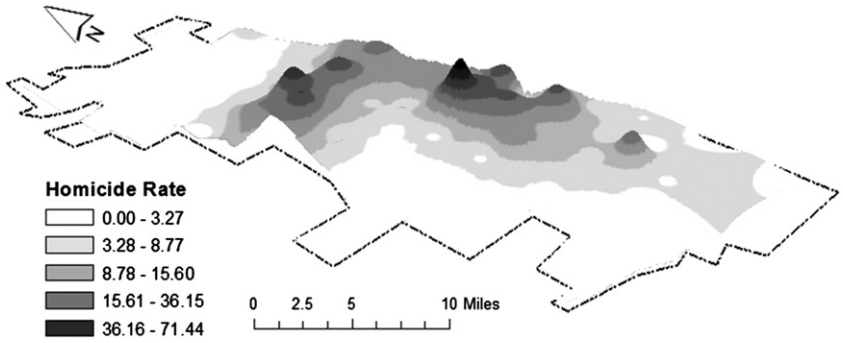

Fig. 1. Homicide rate surface in 1965 (Homicide rate in a community area is calculated by dividing homicide counts to population in that community area then multiplying 1,00,000).