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Temporal stability of model parameters in crime rate analysis: An empirical examination

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ABSTRACT

Two common practices in modeling of crime when crime data is available for multiple years are using single-year crime data corresponding to census data and taking the average of crime rate (or count) over multiple years. Current theoretical and empirical literature provides little, if any, rationale in support of either practice. Averaging multiple years is purported to reduce heterogeneity and minimize the measurement error in the year-to-year emergence of crime. However, it is unclear how useful the analysis of averaged and smoothed data is for revealing the relationship between crimes and socio-demographic and economic characteristics of every single year. In order to more clearly understand these two approaches, this paper applies a seemingly unrelated regression model to assess the temporal stability of model parameters. The model accounts for spatial autocorrelation among crime rates and social disorganization variables at the block group level.

Introduction

A frequent task in spatial modeling of crime is the selection of a dependent variable, either single-year or multi-year average of crime. A number of studies prefer to use a single year and corresponding census data in regression analysis (e.g., Andresen, 2006a; Bjerk, 2010; Chamlin & Cochran, 2004). The purported reason for this, in addition to data availability, is that a gap between the year of census data and crime data may hide potential relationships between crimes and socio-economic characteristics (Andresen, 2006a). Meanwhile, others prefer to smooth crime data by taking the average of crime rates (or counts) over multiple years, in order to reduce the influence of volatility and fluctuation in the year-to-year occurrence of crime. This is, by far, the most common practice; see for example, Browning et al. (2000), Cahill and Mulligan (2003, 2007), Erdogan, Yalçin, and Dereli (2013), Light and Harris (2012), Messner and Golden (1992), Peterson, Krivo, and Harris (2000), Sampson (1985, 1987), and Ye and Wu (2011); for a review see Krivo and Peterson (1996). Admittedly, crime patterns may vary over multiple years, and the location of crime events can also markedly shift over an area's landscape from year to year. In this case, taking average of crimes may help to reduce volatility, wash off the potential effect of outliers, and demonstrate the mean characteristics of crime over a specific time period. To date, however, there is no evidence to support either approach (i.e. single-year or averaging). Lacking a statistical examination of the data, it is unclear to what extent the analysis of these averaged and smoothed secondary data would be useful for revealing the association between crimes and correlates of crime. Averaged crime data may be different with any single-year data, which does not represent any real crime process and may fail to provide meaningful information for understanding the spatial and temporal pattern of crime. This question is of interest and has implications for researchers to make appropriate modeling decisions.

Of particular interest is the potential temporal instability of crime patterns. Criminologists have long been aware of this issue, and within the literature, a frequent strategy used to statistically examine this temporal fluctuation is the difference of means test (e.g., Cahill & Mulligan, 2003; Novak, Hartman, Holsinger, & Turner, 1999). For instance, Cahill and Mulligan (2003) employed a five-year average because the single-year patterns were significantly different (higher or lower) from the five-year average. Admittedly, the difference of means test can test for differences between means

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from several separate groups of crime data. However, in regression analysis of crime, the appropriateness of using single-year or multi-year average crime data should not be purely determined by the appearance of annual fluctuations in crime data itself, but the temporal stability of crime process and characteristics, in other words, the temporal stability of relationships between socio-economic characteristics and crime. This is to say, yearly variation of crime data within a certain range may be accounted for by socio-economic characteristics derived from decennial census data. Therefore, it is necessary to examine the extent to which claims of socio-economic invariance are sensitive to the temporal dynamics of crime data.

This paper attempts to fill this gap in the literature by empirically investigating the temporal stability of model parameters in crime rate analysis, and further assessing the appropriateness of using single-year or multi-year average data in spatial analysis of crime. The case study is violent crime in Columbus, Ohio, using socio-economic data derived from the U.S. Census 2000. We employ seemingly unrelated regressions (SUR) (Davidson & MacKinnon, 1993; Zellner, 1962) to jointly estimate the relationship between 5 single years (1998–2002) and five-year average violent crime rates and socio-demographic variables at the block group level. The Wald statistic test is then used to test the temporal stability of estimated model parameters. With regard to the SUR and Wald test results, if parameters of one group are not significantly different from those of other groups, we can conclude that the crime characteristics are stable across the period considered, and if the average group's performance is worse than other single year groups, there is no basis for using the average measure. Otherwise, the crime characteristics are heterogenous in the study region, and if the average group performs better than other groups, using average measure may help to reduce the volatility and fluctuation within the data.

Context and data sources

Crime data

Our analysis relies on two sets of data, that is, crime data of the city of Columbus and decennial census data. With a population of 711,470 in 2000, Columbus is the capital and the largest city in the state of Ohio, and the 15th largest city in the U.S. Previous research by Browning et al. (2010) indicated that the city of Columbus has characteristics that reflect a wide range of places in the United States from the perspective of population composition, economic functions, commercial and industrial functions. Detailed daily crime data comes from the Columbus Division of Police, and covers a period of 9 years (from 1994 to 2002). Information provided by the dataset includes location of crime incident, date and time when crime happened, date when crime was cleared, Uniform Crime Reporting (UCR) code, and type of crime, among other attributes. Over 160 disaggregated types of crime are available in this large dataset. Criminal offenses are grouped in two main categories in criminology (Ellis & Walsh, 2000), that is, violent crime and property crime. Following FBI's UCR Program, violent crime is composed of four offenses: murder and non-negligent manslaughter, forcible rape, robbery, and aggravated assault. In our dataset, there are in excess of 4000 violent crimes each year.

The dataset provides an accuracy of 95 per cent success rate for the geocoding of violent crime. Remaining unmatched points are addresses erroneously coded by police personnel. With such a high rate of successful matches and the randomness of unmatched points, there are no reasonable concerns about bias in the analysis (Ratcliffe, 2004).

In crime modeling, a large gap between census data and crime data may lead to a failure to explain crime patterns, and the potential relationships between crimes and neighborhood socio-demographic and economic characteristics may be biased (Andresen, 2006a). The most relevant census data for this crime dataset is Census 2000. Therefore, to reduce the magnitude of this gap, the final dataset is selected to include 5 years of data (1998, 1999, 2000, 2001 and 2002). The reason of using 5 years of data is because our data is limited to 2002, so five years includes, in addition to census year data, the two preceding and subsequent years. There are 22,987 violent crimes in total over 5 years: 4099 in 1998, 4415 in 1999, 4647 in 2000, 4944 in 2001, and 4882 in 2002. The violent crime rates in Columbus, which are calculated by dividing the number of violent crimes by the total residential population of the study area, have steadily increased from 6.87 per 1000 population in 1998, to 7.39 per 1000 population in 1999, 7.78 per 1000 population in 2000 and 8.28 per 1000 population in 2001. In 2002 the violent crime rate in Columbus was 8.17 per 1000 population.

Census data

The second dataset is obtained from two institutions. One is the US Census Bureau, which provides Summary File 3 (SF3). The SF3 consists of Census 2000 general demographic, social, economic and housing characteristics compiled from a sample of approximately 19 million housing units (about 1 in 6 households) that received the Census 2000 long-form questionnaire. The SF3 provides independent variables at census block group level. The other data source is the National Historical Geographic Information System (Minnesota Population Center, 2011), which was launched in 2007 and is maintained by the Minnesota Population Center at the University of Minnesota. It is a historical GIS project to create and freely disseminate a database incorporating all available aggregate census information for the U.S. between 1790 and 2010. We use it to create supplementary socio-economic variables.

Spatial unit of analysis

There are numerous ways to create zoning systems (Páez & Scott, 2004), therefore, the modifiable areal unit problem (MAUP) has always been a typical issue in spatial analysis when aggregate geographical data is used. Likewise, the choice of spatial unit (scale) can significantly affect the result of crime analysis (Andresen & Malleson, 2013; Langford & Unwin, 1994). The MAUP can affect indices created from aggregate areal data (Páez & Scott, 2004). Appropriate spatial unit can help reducing the effect of MAUP and ecological fallacy in crime data and socio-economic indicators (Andresen, 2006a; Andresen & Malleson, 2011). Smaller census unit is preferable to large unit because data can be less aggregated and averaged (Oberwittler & Wikström, 2009). Frequently used geographic units in spatial crime analysis are: census tract (e.g., Browning et al., 2010), census block group (e.g., Cahill & Mulligan, 2003), census block (e.g., Bernasco, Block, & Ruiter, 2013), dissemination area (e.g., Law & Quick, 2013), enumeration area (e.g., Andresen, 2006a, 2006b), face block (e.g., Schweitzer, Kim, & Mackin, 1999), street block and more micro spatial units such as street segment (e.g., Weisburd, Groff, & Yang, 2012). Census tract and census block are respectively the largest and smallest census unit in the U.S. Previous research suggests that crime analysis carried out at census tract level may obscure much of the geographic variability that captures violent crime (Cahill & Mulligan, 2003). But census data are not available at census block level. Face block, street block and street segment are commonly used for studying micro built environmental characteristics.

Consequently, in this research we use census block group (BG) which is between the level of census tract and the census block and is the smallest geographical unit for which the U.S. Census Bureau tabulates and publishes sample data. Typically, a BG has a population of 600 to 3000 people. In this paper, the study area does not cover the whole city and the reason is twofold. The first is the contingency of BGs. There are some “holes” (suburbs) in BGs in Columbus. Crime records in these BGs are generally not maintained by Columbus Division of Police which is our crime data source, thus they are excluded from the study area. The other reason is that the U.S. census sets a threshold (100 people in a specific geographic unit) for data availability, which means that census data is only available for those census units having a population more than 100 (U.S. Census Bureau, 2003). In our dataset, four randomly distributed BGs have to be excluded because data are not available for them. As a result, those continuous BGs with available census data are selected as the study area, and there are finally 567 BGs in the study area, out of a total of 571.

Methods

Exploratory spatial data analysis

One of the most common and important tasks in Exploratory Spatial Data Analysis (ESDA) is examining spatial autocorrelation in the data (Rangel, Diniz-Filho, & Bini, 2010). Social science variables are usually positively spatially autocorrelated due to the way phenomena are geographically organized (Griffith, 2003). Therefore, it is necessary to explore the presence of spatial autocorrelation among our variables first. The global Moran's I statistic introduced by Moran (1950) is the most popular measure of spatial autocorrelation, and it takes the form (see Griffith & Amrhein, 1991):

$$I = \frac{n}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij} \left(X_i - \overline{X}\right)\left(X_j - \overline{X}\right)}{\sum_i \left(X_i - \overline{X}\right)^2} \tag{1}$$

where n is the total number of spatial features, X_i and X_j are values for feature i and j, $\overline{X}$ is the mean of X, $(X_i - \overline{X})$ indicates the deviation of i's feature value X_i from its mean $\overline{X}$, and w_{ij} are the elements of the spatial weight matrix, indicating the spatial weight between feature i and j.

Moran's I represents a linear association between a feature value and the spatially weighted average of neighboring values (Ratcliffe, 2010). The expected value of Moran's I statistic is $-1/(n-1)$, which tends to zero as the sample size increases. An I coefficient larger than $-1/(n-1)$ indicates positive spatial autocorrelation, and less than $-1/(n-1)$ indicates negative spatial autocorrelation, and a Moran's I approaching $-1/(n-1)$ indicates an absence of spatial autocorrelation (Griffith & Amrhein, 1991). Hypothesis testing against the null hypothesis of spatial independence can be evaluated by a z-score and p-value. The z-score values associated with a 95 percent confidence level are -1.96 and $+1.96$ standard deviations, indicating that if the computed z-score fall between -1.96 and $+1.96$, the p-value is larger than 0.05, and the spatial autocorrelation is not statistically significant, the observed pattern could very likely be the result of random spatial processes.

Seemingly unrelated regression

We use multiple equation models to estimate yearly relationships between socio-economic characteristics and violent crime, and use a testing method to investigate the stability of these relationships across years. Although we could estimate models for each single year separately and test stability of parameters of each model, it is possible that the models will not be independent due to cross-equation error correlations. Therefore, it is appropriate to take these correlations into account. Zellner's seemingly unrelated regression (Zellner, 1962) is used to estimate models of violent crime rate as a function of a host of social disorganization variables.

As one type of multiple equation regression, seemingly unrelated regression (SUR) is defined as a generalization of a linear regression model that consists of several regression equations. In SUR, a set of equations that have their own dependent and independent variables have cross-equation error correlation, i.e. sharing interdependent unmeasured causes (Light & Harris, 2012). The SUR is performed in two steps. Firstly, ordinary least squares (OLS) is performed to estimate the variance and covariance of cross-equation error term. Secondly, generalized least squares (GLS) is used in the equation system for cross-equation error correlation. Error term's variance and covariance obtained from the residuals of previous OLS regression are used to estimate model parameters. Compared to OLS, SUR is able to provide more efficient and precise estimates of model parameters and standard errors by comprehensively employing all the information in the equation system and considering the interdependent unmeasured causes which can similarly influence violent crime in different years (Zellner, 1962). In addition, it provides a unified framework to test the hypothesis of parameter volatility across equations.

SUR is defined in the following way. Assume that there are M equations in the system. Then, the ith equation is as follows:

$$y_i = X_i\beta_i + \varepsilon_i, \quad i = 1, \ldots, M \tag{2}$$

where i represents the equation number, the i'th equation has a single dependent variable y_i which is an $R\times1$ vector (R is the observation index), X_i is an $R\times k_i$ design matrix, where k_i is the number of regressors, β_i is a $k_i\times1$ vector of the regression coefficients, and ε_i is an $R\times1$ vector which indicates random error terms. All these M vector equations can be stacked, and the SUR system then becomes (Zellner, 1962):

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_M \end{bmatrix} = \begin{bmatrix} X_1 & 0 & \cdots & 0 \\ 0 & X_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & X_M \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_M \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_M \end{bmatrix} \tag{3}$$

Equations (2) and (3) can be written more compactly as:

$$y = X\beta + \varepsilon, \quad \varepsilon \sim N(0, \Omega) \tag{4}$$

where y is an $MR\times1$ vector, X is an $MR\times k$ matrix, β is a $k\times1$ vector and $k = \sum_{i=1}^{M} k_i$, and ε is an $MR\times1$ vector of disturbances.

The model assumes that the error terms ε have cross-equation correlations, that is:

$$E\left(\varepsilon_{is}\varepsilon_{jt}\right) = \begin{cases} \sigma_{ij} & \text{if } s = t, \\ 0 & \text{else} \end{cases}$$

where ε_{is} and ε_{jt} are the error terms of the s'th observation of the i'th equation and the t'th observation of the j'th equation.

The $MR\times1$ disturbance vector can be assumed to have a variance-covariance matrix as follows:

$$\Omega = E\left(\varepsilon\varepsilon'\right) = E\left[\begin{bmatrix}\varepsilon_1\\ \varepsilon_2\\ \vdots\\ \varepsilon_M\end{bmatrix}\left[\varepsilon_1' \quad \cdots \quad \varepsilon_M'\right]\right]$$
$$= E\begin{bmatrix}\varepsilon_1\varepsilon_1' & \varepsilon_1\varepsilon_2' & \cdots & \varepsilon_1\varepsilon_M'\\ \varepsilon_2\varepsilon_1' & \varepsilon_2\varepsilon_2' & \cdots & \vdots\\ \vdots & \vdots & \ddots & \vdots\\ \varepsilon_M\varepsilon_1' & \cdots & \cdots & \varepsilon_M\varepsilon_M'\end{bmatrix}$$
$$= \begin{bmatrix}\sigma_{11}I_R & \sigma_{12}I_R & \cdots & \sigma_{1M}I_R\\ \sigma_{21}I_R & \sigma_{22}I_R & \cdots & \vdots\\ \vdots & \vdots & \ddots & \vdots\\ \sigma_{M1}I_R & \cdots & \cdots & \sigma_{MM}I_R\end{bmatrix} = \sum \otimes I_R \tag{5}$$

where I_R is an R-dimensional identity matrix, $\otimes$ denotes the Kronecker product, and $\sum$ is:

$$\sum \equiv \begin{bmatrix}\sigma_{11} & \sigma_{12} & \cdots & \sigma_{1M}\\ \sigma_{21} & \sigma_{22} & \cdots & \vdots\\ \vdots & \vdots & \ddots & \vdots\\ \sigma_{M1} & \cdots & \cdots & \sigma_{MM}\end{bmatrix} \tag{6}$$

The elements of matrix $\sum$ are estimated using residuals from the OLS regression:

$$\widehat{\sigma}_{ij} = \frac{\widehat{\varepsilon}_i'\widehat{\varepsilon}_j}{R} \tag{7}$$

The GLS estimator of β in equation (4) is given by:

$$\widehat{\beta} = \left(X'\Omega^{-1}X\right)^{-1}X'\Omega^{-1}y \tag{8}$$

And its variance-covariance matrix is:

$$V\left(\widehat{\beta}\right) = \left(X'\Omega^{-1}X\right)^{-1} \tag{9}$$

Anselin (2006) suggested that spatial regression should be employed particularly for studies which use spatially aggregated socio-demographic and economic data. Given the detected spatial autocorrelation in dependent and independent variables (see Table 1), we take spatial effects into account by extending traditional SUR to the SUR with a spatial lag process. We assume a spatial lag effect in the SUR model based on theoretical considerations. Geographical space increasingly plays a core role in crime analysis (Messner & Anselin, 2004). Spatial diffusion processes, for instance, have been consistently found in violent crimes (Cohen & Tita, 1999; Messner et al., 1999; Morenoff & Sampson, 1997; Morenoff, Sampson, & Raudenbush, 2001; Smith, Frazee, & Davison, 2000). In addition, beneficial effects of crime prevention strategies in a neighborhood also diffuse to adjacent neighborhoods (Bowers & Johnson, 2003). This suggests that crime rate and socio-economic characteristics in one spatial unit may be systematically related to those in adjacent units, thus resulting in spatial dependence (Smith et al., 2000). Also, the advantage of embracing a spatial lag process in the SUR model is twofold. First, the correlations among the errors in different equations (also different years) will be utilized to improve the regression estimates. Second, spatial correlation among geographic units will be taken care by spatial lag terms and utilized to improve coefficient estimation. The SUR with spatial lag process can be in a following form:

$$y = \lambda Wy + X\beta + \varepsilon, \quad \varepsilon \sim N(0, \Omega) \tag{10}$$

where W is a R by R matrix of weights with elements w_{ij} represent the proximity of spatial unit i and j. Based on the Queen's 1st order contiguity protocol as suggested by Andresen (2011), a spatial

Table 1
Descriptive statistics for variables used in the analysis (567 observations).

Acronym	Variable description	Mean	S.D.	Min.	Max.	Moran's I[a]
Dependent variables						
VR98	Violent crime rate per 1000 inhabitants in 1998 (log transformed)	0.05	4.56	−11.51	6.10	0.29 (11.59)
VR99	Violent crime rate per 1000 inhabitants in 1999 (log transformed)	0.13	4.53	−11.51	5.80	0.20 (7.88)
VR00	Violent crime rate per 1000 inhabitants in 2000 (log transformed)	0.31	4.39	−11.51	6.66	0.23 (9.18)
VR01	Violent crime rate per 1000 inhabitants in 2001 (log transformed)	0.47	4.30	−11.51	6.91	0.20 (7.90)
VR02	Violent crime rate per 1000 inhabitants in 2002 (log transformed)	0.55	4.13	−11.51	6.10	0.23 (9.02)
AVG	Five-year average violent crime rate per 1000 inhabitants (log transformed)	0.91	3.49	−11.51	6.32	0.24 (9.08)
Independent variables						
POVRTY	Percent of population below the poverty level in 1999	18.52	15.91	0.00	76.81	0.53 (19.45)
UEMPLOY	Percent of population age 16 and over in civilian labor force that is unemployed	3.99	3.42	0.00	30.77	0.25 (10.07)
RENTER	Percent of housing units that are renter occupied	49.77	28.81	0.00	100.00	0.43 (16.18)
NOFAM	Percent of population living in households and are nonrelatives	9.34	8.75	0.00	65.18	0.59 (23.68)
SIGFAM	Number of single-parent families (log transformed)	3.35	2.14	−11.51	5.98	0.29 (10.96)
FOREIGN	Percent of total population that is foreign born	6.09	8.40	0.00	95.86	0.44 (16.47)
HI	Heterogeneity Index	0.33	0.16	0.00	0.76	0.50 (18.95)
$POVRTY^L$	Spatially lagged POVRTY	18.30	11.97	1.18	59.35	0.83 (29.66)
$UEMPLOY^L$	Spatially lagged UEMPLOY	3.97	2.04	0.34	12.36	0.69 (26.51)
$RENTER^L$	Spatially lagged RENTER	49.70	20.14	10.56	98.68	0.78 (27.51)
$NOFAM^L$	Spatially lagged NOFAM	9.15	6.49	3.46	43.43	0.91 (35.59)
$SIGFAM^L$	Spatially lagged SIGFAM	3.38	1.54	−11.51	5.24	0.71 (26.78)
$FOREIGN^L$	Spatially lagged FOREIGN	6.08	5.71	0.00	49.77	0.76 (27.49)
$VR98^L$	Spatially lagged dependent variable VR98	0.19	2.80	−11.51	3.44	0.72 (27.09)
$VR99^L$	Spatially lagged dependent variable VR99	0.38	2.57	−11.51	3.56	0.64 (23.89)
$VR00^L$	Spatially lagged dependent variable VR00	0.54	2.55	−11.51	3.69	0.72 (25.06)
$VR01^L$	Spatially lagged dependent variable VR01	0.66	2.38	−9.18	3.73	0.67 (25.05)
$VR02^L$	Spatially lagged dependent variable VR02	0.79	2.26	−11.51	3.86	0.69 (25.87)
AVG^L	Spatially lagged dependent variable AVG	1.09	2.00	−8.96	3.61	0.73 (27.83)

Note: The numbers in parentheses are z-scores.
[a] We calculate the global Moran's I Index values and z-scores using GeoDa 1.4.0, this is also done by using Queen's 1st contiguity weight which is also created using GeoDa 1.4.0.

weight matrix is created using GeoDa 1.4.0 (Anselin, Syabri, & Kho, 2006). The coefficient λ quantifies the relationship between crime rate y in one BG and crime rates in contiguous BGs. A statistically significant λ can be interpreted as that a spatial diffusion process of crime rate is detected (Doreian, 1980). We calculate the spatial lag of dependent variable $y^L = Wy$ and spatial lag of all independent variables, and apply them in the estimation of the SUR model. The variable y^L can be understood as the "violent crime potential" similar to the "street robbery potential" studied in Smith et al. (2000). As suggested by Tita and Radil (2010), it is feasible to combine the response lag and predictor lag terms in a single model. We use the SUR model with spatial lag process to simultaneously estimate equations using crime rates of different years as dependent variables and all independent variables selected above, in order to obtain the model parameters of each group (i.e. each equation in the model system).

Wald statistic test

A key feature of SUR is that we can test differences between predictors across equations. Based on the estimated parameters of the SUR models, we use the Wald statistic test to investigate whether the correlates of crime vary in their effects on violent crime over time (Clogg, Petkova, & Haritou, 1995). The null hypothesis (H_0) is that the parameter (β_i) for one independent variable in one equation is statistically equal to that of another equation (β_j), that is:

$$\mathrm{H_0}:\ \beta_i = \beta_j$$

$$\mathrm{H_A}:\ \beta_i \neq \beta_j$$

This is the same as testing the following hypothesis:

$$\mathrm{H_0}:\ \beta_i - \beta_j = 0$$

$$\mathrm{H_A}:\ \beta_i - \beta_j \neq 0$$

For testing the null hypothesis, a general formula for the computation of the Wald statistic is as follows:

$$W = \left(\widehat{\beta}_i - \widehat{\beta}_j\right)' \left[var\left(\widehat{\beta}_i\right) + var\left(\widehat{\beta}_j\right)\right]^{-1} \left(\widehat{\beta}_i - \widehat{\beta}_j\right) \tag{11}$$

where β_i and β_j are the parameter vectors including all parameter estimates for two equations, var $(\cdot)$ is the estimated variance-covariance matrix for the parameters. The Wald statistic is asymptotically distributed as χ^2 distribution under the null hypothesis.

If the test fails to reject the null hypothesis at an acceptable level of confidence, it can be interpreted to mean that the parameter of one independent variable in one equation is not significantly different from that corresponding to the same independent variable in other equations. Therefore, the relationship between crime rates and socio-economic characteristics are stable across years, and if the average group's performance is worse than other single year groups, there will be no point in using multi-year average crime rate. Whereas, if the null hypothesis can be rejected at a significant level, model parameters of one equation are significantly different from those of others, it can be interpreted to mean that the relationship is significantly heterogenous over years. In this case, if the average group performs better than other groups, using multi-year average crime rate may help to minimize the impact of annual fluctuations and reduce the potential bias of a single high or low crime year.

Analysis and results

Dependent variables

The present research investigates the appropriateness of dependent variable selection by examining the temporal stability of correlations between socio-economic indicators and violent crime rates. The intent is to test the parameter stability of well-proved socio-economic variables in each single year in order to examine if the criminal processes and characteristics are stable across years. Six dependent variables are used: violent crime rate of the year of 1998, 1999, 2000, 2001, 2002, and five-year average. The reason we investigate violent crime in this study is simply because of the data availability. The reason we use crime rate rather than count is that crime count which measures the quantity of criminal activity is a quite restrictive measure. Andresen (2006a) pointed out that as an absolute term it does not give an indication of why crime happens more in certain places but less in others. We employ the measure of crime rate to evaluate the risk of crime by controlling for the population. The rate is measured per 1000 residential population living in the BG. Violent crime rate in this study is composed of all four violent offenses: murder and non-negligent manslaughter, forcible rape (including intent to rape), robbery, and aggravated assault. The distribution of crime rate is long tailed, and as a matter of practice it is transformed using the natural logarithm (Smith et al., 2000). The transformation also ensures that back transformed estimates of crime rate are strictly positive. Table 1 gives the acronyms (VR98, VR99, VR00, VR01, VR02, AVG), definitions and descriptive statistics for these dependent variables.

Independent variables

The independent variables in this research are selected based on the social disorganization theory (Shaw & McKay, 1942; Sampson & Groves, 1989), one of the most important theories in criminology. Social disorganization refers to "the inability of local communities to realize the common values of their residents" (Bursik, 1988, p. 521). Rooted in social ecology (Park, Burgess, & McKenzie, 1967), social disorganization theory looks for explanations of criminal activity in general characteristics of the social structure and social control on which offenders and victims are embedded. Over the last several decades, a large body of studies has emerged and sought to test the empirical validity of the theory by using multivariate statistical modeling approaches and various crime data sources. They have consistently shown that socio-economic deprivation, residential mobility (or population turnover), family disruption, and ethnic heterogeneity lead to community social disorganization, which in turn, increases violent crime rates (Andresen, 2006a, 2006b; Cahill & Mulligan, 2003; Charron, 2009; Porter & Purser, 2010; Sampson, 1985).

We use a series of variables to capture the four structural elements of the theory: socio-economic deprivation, residential mobility, family disruption, and ethnic heterogeneity. All elements have been recognized to characterize socially disorganized and distressed areas, and have been identified as main sources of social disorganization (Cahill, 2004; Law & Quick, 2013). All variables below are proxy measures of the theory and have been informed by an extensive review of the relevant literature (e.g., Andresen, 2006a, 2006b; Cahill & Mulligan, 2003; Law & Quick, 2013; McCord & Ratcliffe, 2007; Sun, Triplett, & Gainey, 2004; Ye & Wu, 2011). Socio-economic deprivation is measured as percentage of population below the poverty level and percentage of unemployed population. Residential mobility is represented by percentage of renter occupied housing units and percentage of population living in households and are nonrelatives. Family disruption is measured through number of single-parent families. Ethnic heterogeneity is captured by percentage of foreign born population and racial heterogeneity measured by means of the Heterogeneity Index (see equation (12)) which is designed to capture the degree of racial heterogeneity in each BG (Blau, 1977; Cahill & Mulligan, 2003; Sampson & Groves, 1989).

$$\text{Heterogeneity Index} = 1 - \sum p_i^2 \tag{12}$$

where i indicates the number of racial group, p_i is the proportion of the population in a given group (Sampson & Groves, 1989). The index is defined as a function of the different racial groups within a given area, and considers both number of racial groups and population size of each group. The range of the index is (0, 1), within which 0 means maximum homogeneity, and 1 means maximum heterogeneity. We use all 5 different racial groups to generate the index, i.e. White, Black or African American, American Indian and Alaska Native, Asian, and Native Hawaiian and Other Pacific Islander.

In spatial analysis of crime, it is important to consider the spatial dependency in the data. BGs are relatively small geographic units, thus socio-economic characteristics of any BG may not only affect its own crime rate but also crime rates of its neighboring BGs. For this purpose, we also consider the spatial lag of explanatory variables for spatial modeling. Spatial weight matrix is calculated based on the Queen's 1st order contiguity by using GeoDa 1.4.0. Table 1 provides descriptive statistics of all these explanatory variables.

The correlations test (see Table 1 in the Appendix) for all independent variables indicates that none of the pair-wise correlations between explanatory variables is larger than 0.8, which is a common threshold for the issue of collinearity (Andresen, 2006a). The variable of poverty population has a strong positive relationship (0.702) with the spatial lag of itself, the variable of population living in households and are nonrelatives has a strong positive relationship (0.797) with the spatial lag of itself. Both are standard relationships. In addition, the correlations among all six spatially lagged dependent variables are strong. Particularly, the correlations between the spatially lagged 5-year average crime rate and other 5 single years are all strong. However, considering the stable patterns of the geographic distribution of crime rates in 5 years and 5-year average (see Fig. 1), these high correlations can be seen as standard relationships.

Empirical results

Maps showing the spatial distribution of violent crime rates in all five years appear in Fig. 1. All maps are created using ArcGIS 10.1 (ESRI, 2012). The violent crime rate in 1998 shows a pattern of lower crime rate in the northern and southern areas and higher crime rate in the middle areas of the city, especially downtown areas and those found in eastern, western and southern immediate surrounding areas. In other 4 years and 5-year average, the geographic distribution of crime rate shows a similar pattern as in 1998, the BGs with the highest crime rates are those consistently found in downtown areas and in the immediate surrounding areas. The extreme northern, northwest, northeast, southwest, and southeast edges of the city experience very low crime rates. Also, it should be noted that the extreme western BG always belongs to the highest crime rates category in all five years.

The results of global Moran's I indicate significant spatial autocorrelation in violent crime rates (see Table 1). The patterns observed in Fig. 1 are consistent with the test and show that high crime rates tend to be clustered and low crime rates also tend to be clustered. The result also suggests a decreasing spatial autocorrelation of violent crime rate from 1998 to 1999, but a stable spatial autocorrelation from 1999 to 2002. Although it has been suggested that spatial autocorrelation at this level "is not a major issue" (Cahill & Mulligan, 2003, p. 591), for the purpose of unbiased spatial modeling, we believe it is appropriate to adjust for spatial autocorrelation in the analysis.

Following common practice (e.g., Cahill & Mulligan, 2003; Novak et al., 1999), the difference of means test is performed using Stata 11.2 (StataCorp., 2011) to compare crime rates between five single years and five-year average. Table 2 provides the results of paired-samples t-tests. There are three observed yearly fluctuations in crime data, violent crime rates of two single years (1998 and 1999) are significantly lower than the average crime rate, and one year (2001) is significantly higher than the average crime rate. In light of the temporal stability, the common practice followed by the literature as reviewed above would suggest the use of the five-year average measure in this case. However, we propose that the criteria to support the averaging of crime data across multiple years are not only the presence of year-by-year volatility, but also the temporal stability of relationships between socio-economic characteristics and crime.

To verify this, we test the stability of model parameters for the SUR system with respect to socio-economic predictors in the five years under consideration. The SUR and Wald test are performed using Stata 11.2. Table 3 provides the estimation results for the SUR without controlling for spatial effect, i.e. excluding the spatial-lagged dependent variables, and the Moran's I coefficients for residuals in all groups. The results show that Moran's I of residuals in all groups are significant, which indicates the existence of spatial autocorrelation in residuals before any spatial effects were controlled for in the model. This finding suggests that it is necessary to take spatial effects into consideration.

Table 4 provides the estimation results for the SUR system with spatial lag process. Compared to the Table 3, the goodness of fit (as measured by R^2) for all groups are improved. Most importantly, the Moran's I Index values and z-scores of residuals for all groups suggest that the spatial autocorrelation in residuals is not significant anymore. This supports the use of spatially lagged dependent variables in controlling spatial effects in the model. In Table 4, the R^2 is stronger in the case of the 1998 (0.224) and 2002 (0.210) groups. The 1999 group has the lowest R^2 (0.141), lower than the 2000 (0.167), 2001 (0.150) and five-year average (0.152) groups. This is because social-economic conditions have both contemporaneous and lagged effects on crime rates (Rosenfeld & Fornango, 2007). Performance of the five-year average group is lower than the three best performing single year groups. The Breusch–Pagan test of independence suggests that the residuals from the six equations are not independent ($p < 0.001$), which indicates that the SUR estimation is more appropriate in this case.

Results of the Wald statistic test for exploring the model parameter stability of the SUR equation system are shown in Table 5. Only the test for constants of the 1998 group and five-year average group can reject the null hypothesis at a significant level, indicating that the constant differs in its relationship with violent crime rates across the two groups. All other four variables of the two groups fail to reject the null hypothesis at a significant level, suggesting that there are not any significant differences in relationship with violent crime rates across the 1998 and five-year average group for all four independent variables. When comparing other four groups (1999, 2000, 2001, 2002) with the average group respectively, we do not find any significant parameter differences across groups for all independent variables and constants. That is, the association of all independent variables with violent crime rates is not significantly different across these groups. The Wald test in the final column of Table 5 which jointly test all six groups reveals the same fact as before. Therefore, we can conclude that the crime characteristics are stable across five years.

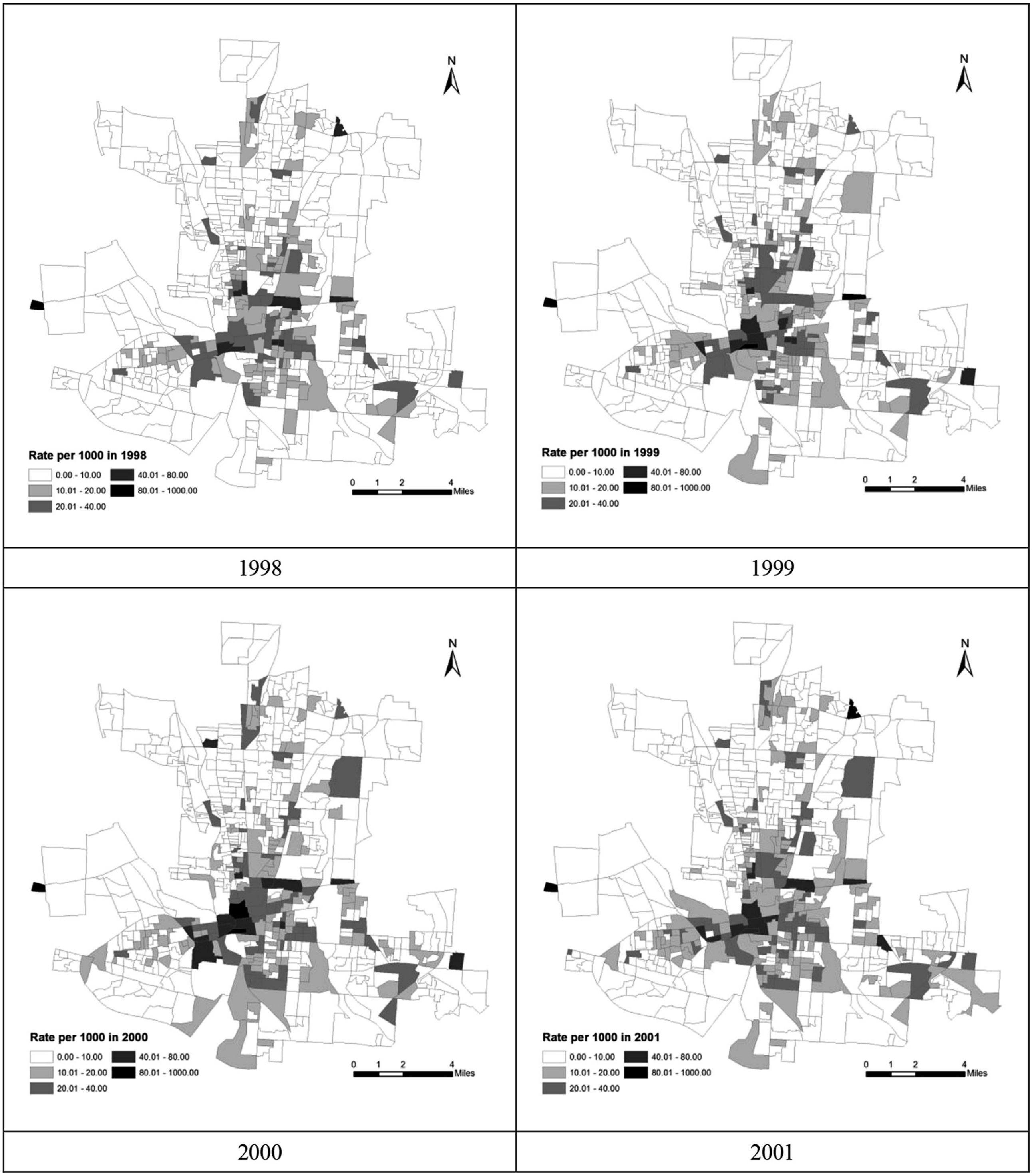

Fig. 1. Violent crime rates per 1000 in Columbus in five single years and five-year average.

Discussion

A synthesis of the results of SUR model and Wald test leads to several relevant conclusions. Of particular importance is that, although the difference of means test suggests significant yearly volatility in crime data, both the SUR model and Wald test show different results. Tables 4 and 5 suggest that there are not any significant differences in relationship with violent crime rates across all single year groups and five-year average group for all four significant explanatory variables. The results also indicate that there is a considerable stability in the signs of the explanatory variables across all groups. In other words, the crime characteristics are stable across five years. This finding yields twofold implications. The first is in regard to the appropriateness of averaging crime data across multiple years. The second is in regard to the selection of dependent variables in spatial analysis of crime.

In previous studies, the main criterion for averaging crime data across multiple years is the presence of annual fluctuation, that is, if

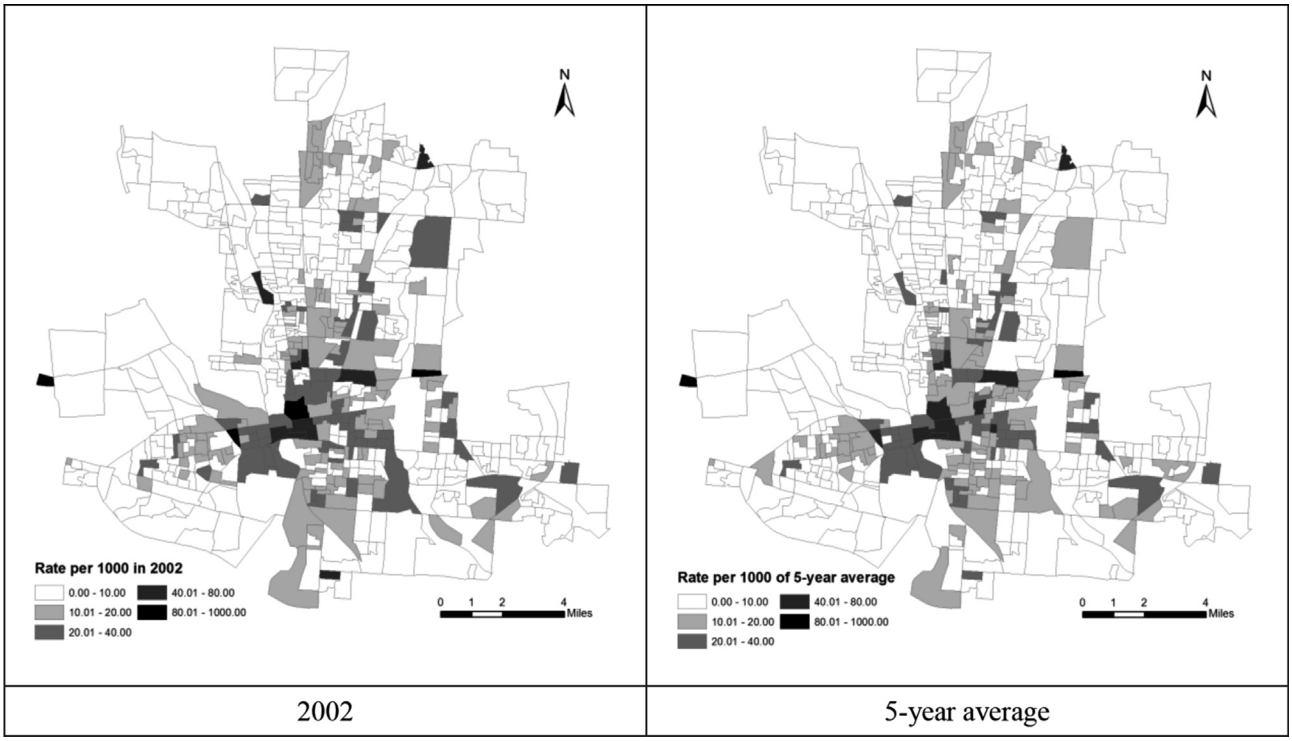

Fig. 1. (*continued*).

Table 2
Results of t-tests of crime rates between five single years and five-year average.

Comparison	Group						t	*p*-Value
	Single year			5-year average				
	M	S.D.	n	M	S.D.	n		
1998 vs. Avg[a]	9.04	20.73	567	10.20	25.17	567	−4.60	<0.001
1999 vs. Avg	9.44	17.59	567	10.20	25.17	567	−1.80	0.037
2000 vs. Avg	10.78	34.19	567	10.20	25.17	567	1.35	0.178
2001 vs. Avg	11.68	43.04	567	10.20	25.17	567	1.84	0.033
2002 vs. Avg	10.51	21.96	567	10.20	25.17	567	1.12	0.265

[a] Avg stands for the 5-year average group.

it is observed by using the difference of means test, crime data of multiple years should be averaged. However, our findings reveal that the criteria to support the averaging of crime data should be not only the presence of year-by-year volatility, but also the temporal stability of relationships between socio-economic characteristics and crime.

Our findings also reveal that averaging crime data across multiple years is not necessarily superior to single year crime rate. Previous studies suggest that in case of the annual fluctuation, using average crime rate is able to reduce the influence of fluctuation in the year-to-year occurrence of crime. But this paper answers an important question of this practice, that is, how useful will the analysis of these averaged data be for revealing the relationship between crimes and socio-demographic and economic

Table 3
Parameter estimates from the SUR without spatial lag and Moran's I of residuals.

Variables	1998	1999	2000	2001	2002	AVG
Constant	−3.212***	−3.462***	−2.854***	−1.667**	−2.637***	−1.084*
POVRTY	–	–	–	–	–	–
UEMPLOY	0.275***	0.318***	0.313***	0.274***	0.307***	0.226***
RENTER	–	–	–	–	–	–
NOFAM	–	–	–	–	–	–
SIGFAM	0.542***	0.472***	0.351**	0.335**	0.433***	0.273**
FOREIGN	–	–	–	–	–	–
HI	–	–	–	–	–	–
$POVRTY^L$	–	–	–	–	–	–
$UEMPLOY^L$	–	–	–	–	–	–
$RENTER^L$	–	–	–	–	–	–
$NOFAM^L$	0.093*	0.126**	0.124**	0.091**	0.118***	0.091**
$SIGFAM^L$	–	–	–	–	–	–
$FOREIGN^L$	−0.132**	−0.114**	−0.109**	−0.190***	−0.132***	−0.134***
Moran's I[a]	0.173 (6.435)	0.069 (2.928)	0.135 (5.678)	0.085 (3.411)	0.111 (4.516)	0.106 (4.264)
R^2	0.111***	0.109***	0.097***	0.120***	0.128***	0.109***
N[b]	567	567	567	567	567	567

Note: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.
[a] We calculate the global Moran's I Index values and z-scores (the numbers in parentheses) for residuals using GeoDa 1.4.0, this is also done by using Queen's 1st contiguity weight.
[b] *N* is the number of observation.

Table 4
Parameter estimates from the SUR with spatial lag and Moran's I of residuals.

Variables	1998	1999	2000	2001	2002	AVG
Constant	−2.356***	−3.095***	−2.473***	−1.575*	−2.409***	−1.034*
POVRTY	–	–	–	–	–	–
UEMPLOY	0.148*	0.274***	0.244***	0.236***	0.241***	0.187***
RENTER	–	–	–	–	–	–
NOFAM	–	–	–	–	–	–
SIGFAM	0.411***	0.413***	0.292**	0.302**	0.375***	0.242**
FOREIGN	–	–	–	–	–	–
HI	–	–	–	–	–	–
$POVRTY^L$	–	–	–	–	–	–
$UEMPLOY^L$	–	–	–	–	–	–
$RENTER^L$	–	–	–	–	–	–
$NOFAM^L$	0.074*	0.111**	0.100**	0.084*	0.106**	0.080**
$SIGFAM^L$	–	–	–	–	–	–
$FOREIGN^L$	−0.103**	−0.103**	−0.088*	−0.173***	−0.116**	−0.119***
Spatially lagged dependent variable	0.473***	0.204**	0.339***	0.195**	0.302***	0.206**
Moran's I[a]	−0.032 (−1.080)	−0.015 (−0.512)	−0.014 (−0.515)	0.008 (0.350)	−0.001 (0.051)	0.020 (0.872)
R^2	0.224***	0.141***	0.167***	0.150***	0.185***	0.152***
N[b]	567	567	567	567	567	567

Note: $^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.
[a] We calculate the global Moran's I Index values and z-scores (the numbers in parentheses) using GeoDa 1.4.0, this is also done by using Queen's 1st contiguity weight.
[b] *N* is the number of observation.

characteristics of every single year. Our analysis suggests that, although the difference of means test indicates that crime rates in 1998 (lower), 1999 (lower) and 2001 (higher) are different from the average crime rate, the results of SUR model and Wald test suggest that all significant independent variables provide statistically identical effects on crime rates of all single years and five-year average. In other words, single-year crime rates can exhibit similar performance in crime modeling analysis as average crime rate. What's more, considering the goodness of fit, the 1998, 2000 and 2002 groups perform better than the average group.

Other key findings of this analysis are as follows. First, in agreement with previous studies, all significant social disorganization variables have the expected signs. To be specific, net of other explanatory variables, (1) socio-economic deprivation which is captured by percentage of unemployed population (UEMPLOY) has a statistically significant, positive association with violent crime rates; (2) residential mobility captured by lag of percentage of population living in households and are nonrelatives ($NOFAM^L$) is significantly and positively related to violent crime rates; (3) family disruption captured by log transformed number of single-parent families (SIGFAM) is also significantly and positively related to violent crime rates; (4) ethnic heterogeneity characterized by lag of percentage of foreign-born population ($FOREIGN^L$) has a statistically significant, negative association with violent crime rates. Among them, socio-economic deprivation is the strongest predictor in the model. In contrast, family disruption's effect on violent crime rates is relatively modest in comparison to other predictors in the model. In addition, the spatially lagged dependent variables are also significantly and positively related to violent crime rates, indicating that proximity to BGs with high rates of violent crime corresponds to higher violent crime rates. This also proves that the consideration of spatial lag effect is necessary for this model.

Second, the spatial lag form of ethnic heterogeneity shows significant impact is because ethnic groups tend to show a cluster pattern. The variable foreign-born population has a high Moran's I value (0.44) with a high z-score (16.47), suggesting that BGs with high percent of foreign-born population tend to significantly cluster across the city. What's more, the Census 2000 shows that population of each ethnic group (White, Black or African American, American Indian and Alaska Native, and Asian) tend to cluster in Columbus, either intentionally or unintentionally.

Third, the percentage of unemployed population, percentage of population living in households and are nonrelatives, and number of single-parent families are modestly stronger for the 1999 group than it is for other five groups, indicating that the socio-economic deprivation, residential mobility and family disruption elements impact violent crime rate in 1999 to a greater extent than crime rates in other years and five-year average.

Fourth, the spatial autocorrelation in the residuals is carefully investigated in this analysis. Comparing the Moran's I Index values and z-scores of residuals in the SUR without controlling spatial effects and the SUR with spatial effects were controlled for, we found that introducing spatially lagged dependent variables into the model are effective in removing the spatial autocorrelation from residuals. This finding indicates the importance of taking spatial effects into consideration.

Whilst this paper addresses one specific issue of the selection of dependent variable, in recent years, a number of other important statistical issues in crime analysis and their impacts on crime analysis have been investigated.[1] For example, the appropriateness of aggregating crime across types (Andresen & Linning, 2012); measure of population at risk (Andresen, 2011); the choice of spatial unit of analysis (Andresen & Malleson, 2013; Jacob, 2006; Ouimet, 2000; Wooldredge, 2002); and the choice of spatial autocorrelation statistic

Table 5
Wald test for parameter stability of the SUR equations.

	98 vs. Avg[a]	99 vs. Avg	00 vs. Avg	01 vs. Avg	02 vs. Avg	All 5 groups
Constant	4.61*	3.76	0.54	1.04	0.98	6.65
UEMPLOY	0.47	2.72	1.24	0.95	1.48	5.99
$NOFAM^L$	0.03	1.07	0.48	0.02	1.15	5.94
SIGFAM	3.09	3.57	0.32	0.48	3.17	2.44
$FOREIGN^L$	0.24	0.27	1.09	3.07	0.02	8.43

Note: $^*p < 0.05$. The null hypothesis of Wald test for the first column is H_0: $\beta_{98} - \beta_{Avg} = 0$, the second column is H_0: $\beta_{99} - \beta_{Avg} = 0$, the third is H_0: $\beta_{00} - \beta_{Avg} = 0$, the fourth is H_0: $\beta_{01} - \beta_{Avg} = 0$, the fifth is H_0: $\beta_{02} - \beta_{Avg} = 0$, and the last is H_0: $\beta_t - \beta_{Avg} = 0$ for $t = 1998, \ldots, 2002$.
[a] Avg stands for the 5-year average group.

[1] These issues were inspired by one of the anonymous reviewer of this paper, we thank the reviewer for this comment.

(Bernasco & Elffers, 2010; Tita & Radil, 2010; Townsley, 2009). Keeping these studies in mind we concentrate only on the selection of dependent variable in this paper. Admittedly, the conclusions we obtained may be influenced by the statistical issues above. For example, first, violent crime rate in this study is composed of all four violent offenses: murder and nonnegligent manslaughter, forcible rape, robbery, and aggravated assault. The temporal stability of model parameters that we found using violent crime rate in this paper needs to be substantiated in the case of property crime or other disaggregated crime types. Second, the census residential population is used as the population at risk when calculating crime rates. Although this is a common practice, recent studies also suggest alternative measures of the population at risk such as the ambient population (Andresen, 2006a). It was found that the use of ambient population has an impact on the results of crime analysis (Andresen, 2011), although Harries (1991) suggested that this improvement is most often not worth the costs in both time and money. Third, in terms of the choice of spatial unit, although some found that it has no impact on the result of crime analysis, see for example, Land, McCall, and Cohen (1990), Ouimet (2000), Wooldredge (2002), and no impact on "the power of the statistical tests performed" (Ouimet, 2000, p. 150), others suggested the use of smaller spatial units (Andresen, 2011). The use of small spatial unit provides stronger coefficients than the larger spatial unit (Ouimet, 2000). The BG is the finest scale for which the U.S. Census Bureau tabulates and publishes sample data. The use of other larger units such as census tract in this study may results in weaker coefficients.

Conclusions

This paper yields several relevant findings. We first present the importance of dependent variable selection, and question the appropriateness of averaging crime rates over multiple years. Although it is a common practice to use either single-year or multi-year average of crime, to our knowledge, evidence to support either practice seems to be absent, as per our comprehensive literature review. A common approach for evaluating the annual fluctuation in crime data is conducting difference of means test for crime data, and averaging crime data across years if fluctuation is observed. However, based on the idea that socio-demographic and economic variables may be able to account for certain degree of fluctuation. By applying a unified modeling framework to assess the stability of model parameters in crime rate analysis, this study adds to existing literature by empirically studying the appropriateness of using single-year and multi-year average measure. First, a difference of means test reveals three significant fluctuation in crime data, that is, crime rates in 1998 (lower), 1999 (lower) and 2001 (higher) are significantly different from the average rate. However, keeping in mind that social indicators may explain and moderate this variation, we present that the criteria to support the averaging of crime data across years are not only the presence of year-by-year volatility, but also the temporal stability of relationships between socio-economic characteristics and crime. To verify this, seemingly unrelated regression is considered a superior approach.

Consequently, by employing comprehensive social disorganization variables, the significant determinants of violent crime rate in Columbus are provided. Based on the estimated parameters of significant variables, the Wald statistic test suggests strong parameter stability between five single years (1998, 1999, 2000, 2001 and 2002) and the average of five years. Although the difference of means test reveals several fluctuations, a more comprehensive regression and model parameters test indicates an inverse result. This implies the importance of taking social indicators into consideration when selecting the form of the dependent variable (i.e. average or single year).

Finally, we conclude that temporal stability refers to not only the year-by-year volatility in crime data, but more importantly, the temporal stability of relationships between socio-economic characteristics and crime. If crime processes are stable over a period of time, and the effects of socio-demographic and economic determinants on crime of different years are significantly stable, it is unnecessary to average crime over multiple years.

Although not the main focus for this research, we also find that the social disorganization theory performs well in explaining violent crime in Columbus. All four elements of the theory are significant, and all variables show expected signs for their estimated parameters. This finding can also add evidence to current empirical research of the theory.

Appendix

Table 1
Correlations for independent variables

X_1	1																		
X_2	0.731	1																	
X_3	0.671	0.689	1																
X_4	0.723	0.678	0.731	1															
X_5	0.730	0.686	0.762	0.769	1														
X_6	0.777	0.798	0.828	0.796	0.845	1													
X_7	0.318	0.344	0.353	0.350	0.343	0.370	1												
X_8	0.373	0.338	0.312	0.328	0.372	0.366	0.379	1											
X_9	0.163	0.205	0.212	0.139	0.192	0.185	0.595	0.269	1										
X_{10}	−0.035	0.015	0.061	−0.012	0.017	0.035	0.484	−0.043	0.531	1									
X_{11}	0.237	0.222	0.132	0.185	0.200	0.161	−0.117	0.130	−0.108	−0.371	1								
X_{12}	−0.105	−0.077	−0.059	−0.170	−0.122	−0.120	0.152	−0.059	0.370	0.171	−0.062	1							
X_{13}	0.198	0.214	0.280	0.159	0.204	0.211	0.183	0.177	0.356	0.022	0.162	0.376	1						
X_{14}	0.443	0.447	0.412	0.449	0.449	0.472	0.702	0.335	0.467	0.469	−0.223	0.046	0.035	1					
X_{15}	0.545	0.548	0.512	0.571	0.582	0.576	0.434	0.422	0.242	−0.011	0.103	−0.169	0.147	0.590	1				
X_{16}	0.245	0.290	0.288	0.216	0.256	0.270	0.501	0.210	0.619	0.543	−0.302	0.233	0.147	0.686	0.344	1			
X_{17}	−0.036	0.044	0.075	−0.024	−0.006	0.053	0.442	−0.010	0.473	0.797	−0.442	0.189	0.000	0.534	−0.037	0.677	1		
X_{18}	0.322	0.350	0.322	0.332	0.356	0.331	−0.036	0.188	−0.114	−0.351	0.359	−0.102	0.219	0.020	0.395	−0.065	−0.416	1	
X_{19}	−0.190	−0.165	−0.168	−0.262	−0.192	−0.229	0.039	−0.153	0.246	0.234	−0.197	0.654	0.212	0.078	−0.213	0.371	0.264	−0.129	1
	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}	X_{13}	X_{14}	X_{15}	X_{16}	X_{17}	X_{18}	X_{19}

Note: X_1: spatially lagged violent crime rate per 1000 in 1998; X_2: spatially lagged violent crime rate per 1000 in 1999; X_3: spatially lagged violent crime rate per 1000 in 2000; X_4: spatially lagged violent crime rate per 1000 in 2001; X_5: spatially lagged violent crime rate per 1000 in 2002; X_6: spatially lagged five-year average crime rate per 1000; X_7: poverty population (%); X_8: unemployment rate (%); X_9: renter occupied housing units (%); X_{10}: population living in households and are nonrelatives (%); X_{11}: single parent families; X_{12}: foreign born population (%); X_{13}: Heterogeneity Index; X_{14}: spatially lagged X_7; X_{15}: spatially lagged X_8; X_{16}: spatially lagged X_9; X_{17}: spatially lagged X_{10}; X_{18}: spatially lagged X_{11}; X_{19}: spatially lagged X_{12}.

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