Spatial Analysis of Metropolitan Area Homicide Rates and their Relationship to Immigrant Growth and Concentration, 1970-2000

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Abstract

This paper examines the effect of metropolitan area immigrant concentration on the metropolitan area homicide rate over a three decade period. A fixed effect panel model is used to correct for unobserved heterogeneity between areas and the spatial clustering of homicide deaths is explicitly incorporated into the model structure. Results from the analysis suggest that the effect of immigration on homicide is time-invariant, and that increased immigration has had a protective effect against homicide in recent decades. The observed spatial clustering of homicide deaths appears to be the consequence of the geographic clustering of unobserved variables, and the spatially-adjusted model is similar to the non-spatial model in both coefficient magnitude and statistical inference.

1. Introduction

The U.S. homicide rate exhibited substantial variation in the latter part of the 20th century, climbing from 7.9 (homicides per 100,000 people) in 1970 to 10.2 in 1980, before non-monotonically falling to a low of 5.5 in 2000.[1] Within the broader national trend, however, there existed substantial geographic heterogeneity in both the level and progression of homicide rates (Harries 1985; Baller et al. 2001). In the context of research methodology, this spatial variation in homicide rates is advantageous, as it allows scholars to develop theories which describe those structural characteristics of places which affect homicide (Messner 1983; Hawley and Messner 1989; Land, McCall, and Cohen 1990; Bursik and Grasmick 1993). One such structural variable, the absence or presence of large immigrant populations, has been the focus of a renewed research interest (Sampson 2008) and is the subject of the present study.

In the period from 1970 to 2000, the U.S. immigrant population increased threefold, rising from less than 10 million to more than 30 million. Foreign born individuals comprised 4.7% of the total U.S. population in 1970; by 2000 this number had risen to 11.1%. This large and growing population segment might be expected to exert substantial influence on social processes. Theories on the potential effects of increased immigration on homicide and other crime rates are well-documented, and have focused on social disorganization and social control (Shaw and McKay 1942; Bursik 1988; Sampson, Raudenbush & Earls 1997), intergroup tensions (Blalock 1967; Hipp et al. 2009), labor market outcomes (Borjas 2003; Card 2005), and changes in demographic composition (Farrington 1986; Moehling & Piehl 2009).[2] Overall, the expected

[1] Source: FBI Uniform Crime Reports. Retrieved on 8/15/2011 from http://www.ucrdatatool.gov.

[2] Mears (2001) provides a thorough accounting of the theoretical bases and practical concerns of the immigrant-crime relationship.

relationship between immigration and homicide is ambiguous, particularly at larger geographic scales; many of the existing theories are most relevant at the neighborhood-level. Macro-level research on the immigration-homicide link has accordingly been inconsistent, with the most common findings an inverse or null relationship (Butcher & Piehl 1998; Phillips 2002; Reid et al. 2005; Ousey and Kubrin 2009; Stowell et al. 2009).

Analyses of homicide and other crime rates which explicitly include spatial effects have been conducted both at the neighborhood-level **(**Morenoff, Sampson, and Raudenbush 2001; Messner and Anselin 2004; Graif and Sampson 2009; Ye and Wu 2011) and at the macro-level (Messner 1983; Baller et al. 2001; Deane et al. 2008). No study has looked at the metropolitan area (MA) association between immigration and homicide using an analysis which has both a temporal and spatial component. This paper will build on the work of Baller et al. (2001), which investigates the spatial relationship between homicide and structural characteristics at the county level, and which suggests that, within certain regions, the clustering of homicide events is related to the clustering of unmeasured variables. In particular, this research will evaluate whether spatial clustering of homicide deaths occurs between metropolitan areas in the United States, assess the pattern of this clustering, and consider how the clustering has changed over time. Any observed spatial clustering will then be incorporated into the analytical framework to answer the primary research question: What is the metropolitan-level effect of immigration on homicide rates, net of other metropolitan-level structural factors, and how has this effect varied over time?

2. Methodology

In a non-spatial ordinary least squares (OLS) analysis of homicide rates, unobserved heterogeneity between MAs may bias regression results. If all potential causal variables are correctly specified in the model, or if any causal variable which is omitted is assumed to be orthogonal to those variables which are included, then unobserved heterogeneity between MAs is unproblematic and coefficient estimates are unbiased. However, the problem of omitted variable bias is likely more salient when looking at an outcome such as homicide, which may be the result of complicated social or family dynamics or difficult to measure but likely MA-variant factors (such as drug market activity).

The longitudinal data used in this analysis contains multiple observations per MA, and this panel structure can be leveraged using a fixed effect (FE) framework to minimize the potential bias from unobserved variables. By focusing on the relationship between the explanatory variables and the homicide rate within MAs, rather than between MAs, the FE model discounts the effect of unobserved heterogeneity between MAs. The coefficient estimate for the foreign born variable, then, can be interpreted as the change in the homicide rate that results from a simultaneous change in the proportion foreign born; the FE model thus provides a causal argument that is stronger than that provided by an otherwise similar cross sectional model.

One important assumption underlying the FE model is that the unobserved heterogeneity between MAs is time-invariant, or equivalently, that the effect of some unobserved factor on the dependent variable for a particular MA does not change over time. In the context of homicide analysis, this assumption may be difficult to uphold, although in some cases dummy variables for different years may accomplish this task. It is also the case that, in this basic FE model, the effect of the observed independent variables on the dependent variable are assumed to be constant over time. A FE model is also unable to produce coefficient estimates for variables which are time-invariant, and, in a related vein, it may be difficult to assess the effects of variables that have little within-MA variation over time.

Data which is geographic in nature, such as the homicide rates from different MAs, complicates the analysis, as potential spatial dependence between the various geographic units alters the functional form of the regression equation. Anselin et al. (2000) describe two types of spatial dependence that are likely to be found in crime data: Spatial autocorrelation, which may be defined as either spatial lag or spatial error, and spatial heterogeneity. This study's primary focus is on the discovery and modeling of spatial autocorrelation.

In an MA-level spatial model of homicide rates, the rate in any particular MA might be expected to depend upon the rates in neighboring MAs, the result of a diffusion process of violence (Baller et al. 2001) and the arbitrary boundaries of most MAs. This diffusion process may be envisioned as the free flow between neighboring MAs of violent individuals, weapons, or ideas. The homicide rate in a specific location may also be dependent on the rates of neighboring locations if an observed causal variable clusters in space. For example, to the extent that immigrants are a causal mechanism behind increased homicide, high homicide rates in a region of the U.S. may be the result of the clustering of MAs with large immigrant populations in that region. This interdependence between neighboring values of the dependent variable is precluded by the standard OLS model, which assumes independence of individual outcomes. To account for such a diffusion mechanism, a spatial lag model, which institutes as an independent variable a weighted value of the homicide rates in neighboring MAs, may be used (Anselin and Bera 1998).

A second type of spatial dependence, spatial error, may be indicated by spatial clustering of the error terms from an OLS model. Spatial error is likely the result of spatial heterogeneity among unobserved or unmeasured variables which are causal or highly correlated with the dependent variable (Baller et al. 2001). Clearly, the inclusion of all potential explanatory variables will serve to minimize geographic heterogeneity among the error terms, yet it may be impossible to accurately measure all covariates. For example, Baller et al. (2001) note that homicide rates may be higher in counties possessing an ideology more accepting of violent behavior, yet cultural norms are extremely difficult to measure or otherwise employ in modeling. The purpose of the spatial error model, then, is to account for the spatial heterogeneity of the error terms by incorporating the neighborhood error matrix into the model estimation.

As described by Anselin et al. (2000), the application of an explicitly spatial regression model is often necessary when dealing with spatial data, as relying on a standard OLS model may result in biased coefficient estimates and/or standard errors of an incorrect magnitude. However, it may be difficult to tell when a spatial regression model is required, and perhaps more importantly, whether a spatial lag model or spatial error model is the appropriate specification. While exploratory spatial data analysis (ESDA), such as the calculation of Moran's I for the included variables, may provide guidance on the former point, it is not helpful for the latter. Instead, the regression diagnostics in GeoDa (Anselin 2005; Anselin, Syabri, and Kho 2006) may be used to determine the correct spatial model.

The particular question under consideration here, which concerns the temporal relationship between an MA's foreign born population and its homicide rate, requires a specification which combines a FE model with a spatial regression model. Unfortunately, GeoDa does not currently have the functionality to deal with longitudinal or panel data. While a longitudinal FE analysis cannot estimate a fixed regional effect, as there is no temporal variation in the regional dummy variable, an observed lag process might vary over time. Thus the application of a spatial lag specification to a panel data analysis would appear to be straightforward: Estimate the spatial lag parameter separately for each time period and then include this term as a regressor in the FE estimation.[3] However, the ability of the FE model to control for unobserved heterogeneity between geographic entities in potential explanatory variables does not extend to heterogeneity among their error terms, rendering the estimation of the spatial error specification problematic. The fact that the observed spatial structure of the error terms is not only present, but may vary over time, further confounds this issue. There is also no obvious test to determine whether the spatial lag model or the spatial error model is the preferred specification, akin to the Lagrange Multiplier tests used in GeoDa to diagnose cross sectional models. In fact, spatial panel data models have been described and constructed in the econometrics literature, yet they are rare in other social science disciplines, and there are no standard estimators available to evaluate such models (see, for example, Elhorst (2003) and Kapoor, Kelejian, and Prucha (2007) for spatial panel data model specifications). Instead the approach taken here is a combination model using the diagnostic tools available in GeoDa, along with a fixed panel specification in Stata. Specifically, the analysis will proceed as follows:

1. Exploratory spatial data analysis will be used to detect whether the data exhibits cross sectional spatial autocorrelation separately for each decade. Based on the work of Baller et al. (2001) the expectation is that spatial autocorrelation will be observed in all decades.
2. Re-run the models using the appropriate spatial specification in GeoDa and save the predicted values from these analyses.

[3] In practice the process is likely more complicated, as the weighted lag term may be endogenous within the regression equation, requiring an instrumental variable approach (Land and Deane 1992). Ward and Gleditsch (2008) also highlight the potential for temporal serial correlation in the spatially lagged dependent variable, but this is less likely to be an obstacle in a fixed effect model, which is concerned not with the actual value of the lagged variable, but with its first difference.

3. Separately regress, using panel fixed effects models: 1) a non-spatial model of the observed homicide rates on the original explanatory variables, 2) the predicted values from the non-spatial OLS model on the original explanatory variables and, 3) the predicted values from the spatial error model on the original explanatory variables.
4. A comparison of these results, with particular attention to the differences between the OLS predicted value panel coefficients and the spatial error predicted value panel coefficients.

This paper is situated closely to the work of Baller et al. (2001) with some important differences, most notably the focus on the foreign born population, a variable that was not considered in this prior analysis. This exclusion is possibly a result of the historically low levels of immigration during the 1960's and 1970's, levels which had increased greatly by 2000. By 2000, foreign born individuals comprised over 11% of the U.S. population, and the effect of this growing population segment might be expected to exert more of an influence on social processes.[4] The FE methodology used here, which highlights the effect on homicide rates of shifts in the explanatory variables, is also distinct from the repeated cross-sectional analyses used by these authors, as is the focus on metropolitan areas, rather than counties.

3. Data

This paper considers the relationship between immigration and homicide mortality at the level of the metropolitan area. Metropolitan areas (MAs) are U.S. Office of Management and

[4] Source: U.S. Census Bureau. Retrieved on 8/24/2011 from http://www.census.gov/population/www/documentation/twps0081/twps0081.html.

Budget-defined geographic entities, consisting of an urbanized central county or county-equivalent and any neighboring counties which have close economic and social ties to the central county. Although MAs are always defined at the county level[5], the constituent counties of an MA may change over time with population redistributions and the shifting of the economic and social ties. In order to ensure that the estimates of the immigration/homicide relationship are not unduly influenced by changes in the constituent counties of an MA, a consistent MA definition, based on the county structure in 2008, is utilized throughout the period of the study.[6] Because they are geographically removed from the continental United States, MAs in Alaska and Hawaii are not considered in this analysis.

The choice of the geographical unit to study is quite relevant in a spatial analysis, as the spatial relationship may vary depending on the geographic scale. In their county-based study, Baller et al. (2001) note that their chosen analytical scale could either be too large or too small, obscuring important geographic variation or possibly creating it. The same caveat applies here, although there is theoretical justification for why MAs are an appealing geographic scale for this type of research. Although MAs have no true municipal function, they are the statistical equivalent of what is colloquially known as a "city". The interpretation of some causal mechanisms often used in homicide studies, such as labor markets or residential stability, may be best modeled at this level. There is also precedence for the use of MAs in the study of the structural determinants of homicide (Messner 1983; Stowell et al. 2009). In a broad sense, the use by researchers of a number of different geographic scales in studies with similar theoretical

[5] In the states of New England, MAs were once constructed at the city/town level; this distinction is irrelevant here.

[6] As of 2000, these geographic entities became known as "core based statistical areas" or "metropolitan divisions". The more widely recognized and colloquially used "metropolitan area" is employed throughout this paper, although this term refers to what are now considered "metropolitan divisions".

foundations and variable compositions allows for post-hoc analysis of strengths and limitations of each scale. It is worthwhile to recognize that the results obtained here are predicated on the use of MA as the unit of analysis.

The dependant variable is the homicide rate, defined here as the average number of homicide deaths per MA over the three year period centered on each decadal census (e.g. 1999-2001 for the 2000 decade) divided by the total MA population from the census. The three year average is used to provide smoothed rates, for which the influence of exceptionally high or low homicide years is minimized. Homicide rates were calculated for each decade from 1970-2000. Homicide deaths were identified using restricted mortality cause-of-death files from the National Center Health Statistics. These files contain a record for every death that occurred in the United States and include the ICD code for the cause of death, allowing homicide deaths to be isolated. These restricted files also include the county of residence of each homicide victim, from which the MA homicide counts are constructed.[7] Total MA population figures were aggregated from county-level data obtained from the National Historical Geographic Information System (Minnesota Population Center 2004), as were all independent variables, except where noted.

Many of the explanatory variables included in the model are consistent with those that have been used in prior studies of the immigration/homicide relationship. Principal component analysis is used when necessary to allow the incorporation of potentially collinear variables. The primary independent variable of interest, immigrant concentration, is measured by calculating the proportion of each MA that is foreign born and the proportion of each MA that is Hispanic and summing the z-scores of these figures. The use of an index to measure immigrant

[7] Although the counts are constructed using the MA of residence of the victim, rather than the location of the homicide occurrence, these numbers are likely to be very comparable for large geographic entities such as MAs.

concentration is common in this literature (Morenoff, Sampson, and Raudenbush 2001; Ousey and Kubrin 2009; Stowell et al. 2009), and reflects the high correlation of these two variables throughout the study period.

Economic disadvantage, widely associated with an increased incidence of homicide, is measured as an index of the mean MA inflation-adjusted household income, the proportion of the MA population that is below the poverty level, and the proportion of the MA population that does not have a high school diploma. The proportion of the MA population that is non-Hispanic black, sometimes included in the economic resources index, does not load heavily on that factor here and is included as a separate covariate.

Homicide rates may also vary depending on the age or family structure of an area. The adult to child ratio, calculated as the total population 18 years or older divided by the total population under the age of 18 is a measure of informal social control. The divorce rate is a measure of familial social control, and is computed as the total population that is currently divorced divided by the total population 15 years or older. The proportion of the MA population that is male and between the ages of 15 and 24 is included to reflect MA-level heterogeneity in the age-gender group at the highest risk of becoming a homicide victim.

The majority of homicides are committed with firearms and the magnitude of this number changed little during the 1970-2000 period.[8] The stability of firearm homicide deaths over time may obscure geographic variation in the incidence of such deaths, and geographic heterogeneity in firearm prevalence could therefore be an important explanatory variable behind geographic fluctuations in homicide rates. Greater firearm availability increases the risk that a firearm is

[8] In the full NCHS data (not limited to homicides which occurred in MA's), the percentage of homicides committed with firearms was 67.7% in 1969-1971, 64.7% in 1979-1981, 66.0% in 1989-1991, and 64.7% in 1999-2001.

impulsively used in a domestic altercation, or that a firearm is present during robberies or other crimes that may result in death. Firearm availability is likely the outcome of state regulations, such as required background checks or waiting periods for purchase, and there may be regional variation in the acceptability of guns and gun ownership. While the actual prevalence of firearms may be difficult to ascertain, Azrael, Cook, and Miller (2004) have advocated that the proportion of suicide deaths that were committed using a firearm be used as a proxy for gun ownership. This measure, also constructed using the NCHS mortality data, is employed here to account both for differences between MAs in gun ownership and differences within an MA in gun ownership over time.

The substantial drop in crime rates during the 1990's was potentially influenced by increased policing, highlighting the importance of controlling for police force size in the FE portion of this analysis (Levitt 2004). Data on the number of sworn officers per police agency were obtained from the FBI's Law Enforcement Officers Killed and Assaulted program. These data were aggregated to the MA level based on the Agency Identifier Crosswalk available from the National Archive of Criminal Justice Data (2005). In addition to the above variables, the cross-sectional OLS and spatial error models will include regional dummy variables to control for the existence of broad spatial regimes. The FE analyses will also incorporate decadal dummy variables to account for any secular trends in homicide rates.

This analysis is limited to MAs which had a population greater than 25,000 in each of the four decades under study. Of the MAs which achieved this population threshold, 29 had excessively large group-quartered populations in one or more decades; these areas were removed from the analysis, leaving a total sample of 349 MAs.[9] In all decades combined, nearly 88% of homicide deaths were individuals who resided in an MA, and approximately 98% of these deaths are incorporated in the final sample.

4. Analysis and Exploratory Spatial Data Analysis (ESDA)

A weight matrix is a required element for all spatial analyses and the results from any analysis are dependent upon the specific weight matrix chosen. The definition of neighbor may vary depending on the scale of the geographic area under study, the expected process under consideration, and the precise question that is being asked. As the neighbor definition, and by extension the weight matrix, is central to the estimation of the spatial regression models, its construction should be theoretically sound. In most instances, however, scholars defer to Tobler's first law of geography (Tobler 1970), and define neighbors as those entities that are the most spatially proximal, with neighbor importance decreasing with distance. However, it is noted that spatial proximity is certainly not the only, and may not always be the most desirable, way in which to define neighbors.[10]

This research, which focuses on relationships between metropolitan areas, utilizes a rook weighting scheme, in which adjacent MAs are considered neighbors. Non-adjacent MAs are considered non-neighbors to the origin MA and do not explicitly contribute to calculations

[9] "Excessively large" is defined here as a group-quartered population that was more than 2 standard deviations above the mean for all MAs. These are generally small MAs which include large universities (e.g. Ithaca, New York) or military installations (e.g. Jacksonville, North Carolina), and which exhibit outlying values on many of the included explanatory variables.

[10] Tita and Radil (2011) present an analysis which relies on a spatial weight matrix with an explicitly conceptual definition.

involving the origin MA. It is fairly plain to see, however, that if area B is adjacent to area A and area C is adjacent to area B (but not area A), that area C may implicitly be affected by area A through the effect of A on B and B on C. This is the process of diffusion through which a spatial process might be expected to occur.

While MAs may be contiguous in some parts of the United States, there are other parts of the country where a single MA may not be contiguous to any other. To ensure that every MA has at least one neighbor, Thiessen polygons were constructed from the centroid of each MA, and the rook contiguity rule was used to define neighbors based on the Thiessen polygon structure. Each Thiessen polygon corresponds to an MA and includes all of the points in the continental U.S. that are closer to the centroid of that MA than to the centroid of any other MA. The use of this transformation, which does not substantively alter the concept of a rook matrix (which is based on adjacency, rather than distance), results in a fully connected space of MA polygons. Under this weighting rule, nearly all MAs have between 4 and 8 neighbors, and the majority have either 5 or 6 neighbors.

The first step in the ESDA is to determine whether there is overall spatial dependence among MA homicide rates in the data. This can be assessed using the well known Moran's I statistic and scatter plots which graph the lagged (neighbor-weighted) homicide rate of an MA as a function of its own homicide rate (Anselin 2005). The scatter plots in Figure 1 show that MAs with high homicide rates tend to neighbor MAs with high homicide rates, indicated by the positive slope of the accompanying fitted regression line. Although the scatter patterns are similar over all four decades, the plot in 2000 appears more densely compressed than those in other years, perhaps suggesting increased homogeneity in MA homicide rates during this decade. While these are not true Moran scatter plots, which are mean-centered and standardized, they are conceptually equivalent and provide identical inference: There is significant spatial dependence among MA homicide rates in all of the four decades under study.[11] The spatial dependence of homicide rates is perhaps not surprising, given that such dependence has been observed in prior research (Baller et al. 2001; Graif and Sampson 2009), but it is important to document that this dependence exists at the level of the MA as well as the smaller geographies used in those studies.

The global Moran's I statistics report that spatial dependence is present in the data, but do not indicate the pattern of the dependence or specify which MAs are contributing heavily to the overall dependence. To reveal clusters of high or low homicide MAs, it is necessary to use a local indicator of spatial association, one of which is the local Moran's I. The local Moran's I is a decomposition of the global Moran's I into the contribution of each MA, and comparisons between the local Moran's I values for individual MAs may indicate clustering of high homicide MAs with other high homicide MAs or low homicide MAs with other low homicide MA's (see Anselin (1995) for technical details regarding the local Moran's I). The choropleth maps shown in Figure 2 indicate clusters of low homicide MAs in gray and clusters of high homicide MAs in black; MAs in white are not part of significant clusters in each decade.

In all of the four decades under study, high homicide rates are clustered in southern MAs, with some smaller clusters existing in California in 1980 and in the Chicago area in 2000. The overall pattern of high MA homicide clustering appears to be similar between decades, although there is a noticeable shift of high homicide areas out of Florida and Texas over time. Low homicide MAs are clustered in the northeast and the north-central parts of the country; these clusters also show little change over time. While the local Moran's I also allows for the

[11] The corresponding Moran's I statistics are 0.504 in 1970, 0.481 in 1980, 0.407 in 1990, and 0.404 in 2000. Each is statistically significant at the .001 level, based on the random permutation procedure outlined in Anselin (2005).

identification of “outlying” areas, either high homicide MAs that are surrounded by low homicides MAs or vice versa, there are typically few of these outliers in any decade and they are regarded here as non-clustered.

In this presentation of the homicide rate clustering suggested by the local Moran’s I, it is important to recognize that these maps are based on the univariate distribution of homicide rates, and do not take into account other structural variables that may vary between MAs. The high homicide rates exhibited by southern MAs would, *ceteris paribus*, suggest that the South is particularly dangerous, yet all other things are likely not equal. Clusters of high homicide MAs may be the result of clustering of any other variable, observed or unobserved, that is associated with increased levels of homicide, such as economic disadvantage, gun prevalence, or cultural influence. While these maps convey information about relative levels of homicide risk in various parts of the country, they are not designed to account for these other factors. For this, regression modeling is used.

4.2 OLS Regression by Decade

Table 1 contains the coefficients from the ordinary least squares regressions of homicide rates on MA structural variables, estimated separately for each decade. The cross-sectional nature of these models prevents any causal inference from being made, but the coefficients are largely as expected. Both the foreign born index and the proportion non-Hispanic black are significant (except the foreign born index in 2000) and positively associated with higher homicide rates. Likewise, increased economic disadvantage and increased divorce rates predict increased levels of homicide. The gun prevalence ratio is positive and significant in three of the four decades, suggesting that the number of guns in the community may impact (or be impacted by) the homicide rate. Policing levels also exhibit a significant association with murder rates; this is almost certainly a response by high homicide MAs in greater police employment.

Consistent with the results from Baller et al. (2001), the South variable has a significant coefficient in 1970 and 1980, although this significance disappears in 1990 and 2000. In fact, in 2000 the regional dummy variables that show a positive and significant sign are those for the Midwest and the West. Note that this does not imply higher homicide rates in the Midwest and West regions in 2000; rather, the significant coefficients indicate that these two regions exhibited increased homicide rates net of the other explanatory variables in the model. The higher absolute rates in the South (see Table 2), then, appear to be explained largely by the variables included in the model, at least in 1990 and 2000. Furthermore, the significance of the Midwest and West variables suggests a presence in these regions of some unmeasured variable which exhibits a positive association with homicide rates. The use of the regional dummy variables in the cross-sectional models thus seems to be helpful in controlling for some of the geographic heterogeneity that is displayed in the clustering maps.

Fit statistics for each of the decadal OLS models are also reported in Table 1. The high R-squared values in each decade indicate that the included explanatory variables explain the variation in homicide rates fairly well. The log likelihood, Akaike info criterion (AIC), and Schwarz criterion are additional measures of fit that will be used in the comparison of the OLS models to the spatial models presented next. As described in Anselin (2005), better fit is defined by a higher log likelihood, a lower AIC, and a lower Schwarz criterion. The Schwarz criterion is similar to the AIC, with additional model parameters (which increase the log likelihood) penalized more heavily.

In addition to the standard statistics of model fit, the GeoDa software package computes spatial diagnostics, which indicate the absence or presence of spatial autocorrelation in the OLS model and suggest the correct spatial model with which to proceed. The decision rule for the choice of spatial regression model is based on the Lagrange Multiplier (LM) statistic, calculated separately for a spatial lag specification and a spatial error specification, in both a standard and robust form.[12] The results from these diagnostic tests are shown in Table 3, along with the Moran's I value for the residuals from the OLS regression.[13] The Moran's I value is significant in each year, denoting the presence of spatial autocorrelation that could, if left uncorrected as in the OLS model, bias coefficient estimates or result in imprecise standard errors. Each LM model specification is shown with its p-value for each decade, indicating the significance of the LM statistic in that year. In all four decades, the spatial error model is the preferred specification; subsequent analyses will therefore focus on correcting for the spatial autocorrelation with a spatial error specification.

The selection of a spatial error specification is backed by a strong theoretical foundation as well. Recall from the prior discussion of spatial models that the spatial error alternative suggests spatial autocorrelation that is the result of the geographic clustering of unobserved variables, while the spatial lag alternative suggests a process of diffusion between neighboring geographic areas. While a diffusion process of homicides is a fairly common argument in studies which utilize a smaller geographic scale (e.g. census tracts or similarly defined neighborhoods), it is less conceptually appealing when looking at MAs. The greater geographic

[12] The construction of the LM statistic is explained in detail in Anselin et al. (1996). The decision rule is outlined in Anselin (2005).

[13] This is a different Moran's I calculation than that performed in the ESDA section of this paper, which was based on the observed values of the homicide rates.

distance, limited transportation links, and weaker social networks between MAs, relative to neighborhoods, would appear to make an MA homicide diffusion process less likely.

4.3 Spatial Error Regression by Decade

Table 4 displays the coefficients from the spatial error regression models, estimated separately for each decade. With few exceptions, these results are similar to those from the OLS model listed above. This is perhaps unsurprising, as the spatial error correction primarily influences the precision of the model standard errors, and few of the estimates in Table 1 were marginally significant. The noticeable differences between Tables 4 and 1 are the loss of significance of the foreign born index in 1970, the loss of significance for the Midwest variable in 2000, and the new significance of the adult to child ratio in 1980. In the table, lambda refers to the spatial autoregressive term, which defines the spatial correlation among the error terms; this term is significant in all four decades.

While the R-squared terms are not equivalent between the OLS and spatial error models, a comparison of the remaining fit statistics from Tables 1 and 4, shows an improved model fit under the spatial error model. In each of the four decades, the log likelihood of the spatial error model is higher (less negative) than the corresponding figure for the OLS model. Likewise, the AIC and Schwarz criterion measures are both lower in the spatial error model than in the baseline regression.[14]

[14] Two additional diagnostics are provided by GeoDa: The Breusch-Pagan (BP) test for heteroskedasticity and a Likelihood Ratio Test (LRT) of the spatial autoregressive coefficient. While the BP test suggests that heteroskedasticity may still remain in the model, the LRT, and its relation to the LM statistic and z-score for the spatial autoregressive coefficient in Table 4, does not indicate serious model misspecification problems (see Anselin 2005).

4.4 Fixed Effect Regression

The coefficient estimates from the spatial error models show the association between each explanatory variable and the homicide rate at decadal intervals after appropriately controlling for the spatial clustering of homicide rates. The aim of this paper, however, is to demonstrate how *changes* in each explanatory variable, and the foreign born index in particular, are reflected in *changes* in the homicide rate. To this end, the predicted values from the cross-sectional spatial error models will be used as spatially-corrected dependent variables in a FE regression model. As noted prior, the FE model relies on within-MA variation of the model parameters, rather than between-MA differences in model parameters, in the estimation of coefficients. As such, the implicit inclusion of between-MA explanatory variable variation in the predicted values becomes inconsequential. Importantly, however, for the purposes of this paper, the predicted values from the spatial error models may properly be considered as homicide rates into which the decade-specific spatial correlation of the error terms has been incorporated.

Prior to estimating the spatially-corrected FE model, it may be instructive to look at the non-spatial formulation. There exists a paucity of longitudinal research on the structural covariates of homicide rates generally, and the immigration-homicide link specifically, and the results from this analysis, while not accounting for the spatial patterning of homicides, may add to this limited existing knowledge. The coefficients from this non-spatial FE model are displayed in the first column of Table 5.

In contrast to the positive coefficient on the immigration variable in the cross-sectional regressions reported in Tables 1 and 4, the foreign born index exhibits a negative coefficient in the FE model, with increases in the foreign born population associated with decreases in homicide rates. Reductions in the homicide rate are also indicated in those MAs in which the adult to child ratio and the number of police per capita are increased; both of these results conform to theoretical expectations. The gun prevalence ratio, computed as the proportion of suicides in which a firearm was used, is positively associated with homicide rates. Although the coefficient on this variable is quite small, its significance implies that the broad gun reduction strategies employed by some police departments may be effective in reducing the threat of homicide. There are also otherwise unexplained period effects in the analysis of homicide rates; the decades of 1980 and 1990 both exhibit higher rates, after controlling for the other covariates, than does the reference decade of 1970.

The spatially-corrected FE model relies on the predicted values from the spatial error models and, as such, may not be directly comparable to the FE model based on the observed homicide rates. In order to create an equivalent model with which to compare the spatial FE model, the predicted values from the cross-sectional OLS models are used as the dependent variable in a non-spatial FE model. The coefficients from this model are shown in column 2 of Table 5, and the coefficients from the FE analysis of the predicted values of the cross-sectional spatial error specification are shown in column 3. There are few noticeable differences between the coefficients of these two models, although the variable for 1980 has achieved significance in the spatially-corrected analysis. The primary variable of interest, the foreign born index, is not statistically significant in the spatial error model. Many of the remaining covariates exhibit the expected sign, with economic disadvantage, the proportion non-Hispanic black, the divorce rate, and the gun prevalence rate associated with higher predicted homicide rates. Surprisingly, the proportion of the population that is young and male is negatively associated with predicted homicide rates. Neither the adult to child ratio nor the police rate has a significant effect on the homicide outcome. There are also significantly lower predicted homicide rates in 2000, net of the other covariates, relative to the other decades.

4.5 Temporal Variation in the Fixed Effect Model

The process through which homicide rates are affected by the structural covariates in this study (as well as by other unobserved variables) might be expected to change over time. The coefficients from the FE estimation, however, are essentially "averages" of the effects between all periods and, as such, may obscure temporal heterogeneity in the relationships between the characteristics of the MAs and their homicide rates. This may be of particular importance in a study such as this, in which the data panels are chronologically distant. To assess the temporal stability of the coefficient estimates from the spatially-corrected model and the corresponding non-spatial model, the full models are disaggregated and rerun as three separate 2-period FE analyses for the decades spanning 1970-1980, 1980-1990, and 1990-2000. A 2-period FE is equivalent to a first-difference model, with the difference in homicide rates between period 1 and period 2 expressed as the difference in the MA structural characteristics during this time. The coefficients from each decadal estimation are shown in Table 6.

The separation of the analyses by time period presents a very different picture of the effect of some of the explanatory variables on the MA homicide rate. Notably, the insignificance of the foreign born index in the full spatially-corrected model, shown in the third column of Table 5, appears to be the consequence of variation in the effect of that variable over time. The coefficient on this immigration variable switches sign over the study period, indicating a positive association between immigration and homicide prior to 1980 and a negative association after that date. A change in the directionality of an effect is also apparent for the police rate, which becomes negative in 1990 after having a positive association over the first two decades. None of the year dummies have a significant sign in these disaggregated models, suggesting that variation in homicide rates is not being driven by period effects not otherwise accounted for in the model.

Because the outcomes of the spatial regressions are dependent on the spatial weight matrix that is used, two additional analyses were performed using alternative weight matrices. Only the coefficients from the disaggregated spatially-corrected FE model, corresponding to the last three columns of Table 6, are shown in Table 7. In the first three columns of Table 7, a second order rook contiguity matrix is used; under this specification, an individual MA's neighbors include those MAs directly adjacent to it as well as those MAs adjacent to the directly adjacent MAs. Adjacency is again determined using the Thiessen polygons, as in the main analysis. In the last three columns of Table 7, a distance weight matrix is used; under this specification all MAs within a specified distance of an individual MA are considered as its neighbors. The cutoff distance employed here, based on the actual geographic location of the centroid of each MA, is approximately 250 miles. While there are some differences in the significance levels and coefficient magnitudes of some variables in these alternative specifications, relative to the initial model, the basic patterns are the same, signifying that the model is robust to the chosen weight matrix.

5. Discussion

In developing this paper, two themes were of paramount importance: 1) A focus on within-MA change in homicide rates and the variables which elicit that change and 2) appropriately accounting for the potential spatial dependence of homicide events.

5.1 Comparison of the cross-sectional models and the FE model

The importance of focusing on within-MA change can be seen by contrasting the results from the cross-sectional analyses displayed in Table 1 with the results from the FE model in column 1 of Table 5. Looking first at the foreign-born index, the positive coefficients in the cross-sectional analyses from 1970 to 1990 imply that, even after controlling for economic factors, immigrants tend to live in MAs that have higher homicide risks. This statement may not be particularly surprising, and may, in fact, be the consequence of immigrants self-selecting into high-homicide MAs, or being drawn to them based on familial obligations or other unobserved factors. The FE model, however, presents a stronger causative argument for the effect of immigration on homicide levels, as *increases* in the foreign born population are associated with *decreases* in the MA homicide rate, at least over the later years of the study. The unobserved factors which may be drawing immigrants to a specific MA become irrelevant in the FE model, at least to the extent that these factors are time-invariant. While the time-invariance of the unobserved heterogeneity between MAs is an open question, the covariates used in this study are consistent with those used in prior studies, and explain a substantial amount of the between-MA variation in homicide rates.

The comparison of the results from the cross-sectional and FE models is also noteworthy for the population structure and police rate variables, which have substantially different interpretations in the FE model. Both of these variables are positively associated with homicide rates in most of the decadal cross-sections, indicating that larger MAs are likely to have increased homicide rates and that MAs with high homicide rates are likely to have a greater police presence. The negative FE coefficient for the population structure variable, however, suggests that growth may result in lowered rates of homicide, and the negative coefficient for the police rate variable implies that police force size is an effective deterrent against this type of violent crime.

Some of the remaining variables that were shown to be correlated with homicide rates in the cross-sectional models are no longer significant in the FE model. Because the FE model estimates based on within-MA variation, structural factors that remain constant, or nearly constant, from one decade to the next are unlikely to be statistically significant in the FE model. This may explain why the proportion young male and economic disadvantage variables are not significant in the FE model; these variables are largely time-invariant. It is, of course, possible (and likely, based on the cross-sectional OLS estimates) that these variables exhibit substantial between-MA variation. These variables, and their between-MA variance, will contribute to the spatially-corrected model through their effects on the homicide rates in the cross-sectional spatial errors models; these effects are implicitly incorporated into the predicted values used in the spatially-corrected model.

5.2 Comparison of the spatial and non-spatial models

Although spatial autocorrelation was evident in the diagnostics performed on the OLS models, the results from the spatial error cross-sectional regressions are, in general, quite similar to the results from the OLS regressions. This is unsurprising, as the spatial error specification will be primarily reflected in the estimated standard errors, rather than the coefficients themselves. There is little evidence that a spatial diffusion process of homicide exists between MAs, an outcome that, as suggested in the results section above, is also not unexpected. The process of diffusion, which may be related to spillover effects or retaliation effects, is likely to be more relevant at a smaller geographic scale. While Baller et al. (2001) employ a spatial lag model in their study, at least for the southern subset of their data, their data is aggregated at the county level. Since MAs are typically composed of more than one county, the homicide diffusion that these authors discern may exist between adjacent counties within the same MA, and thus obscured in the data used here.[15]

A comparison of the results from the FE models of the OLS predicted values and the spatial error predicted values, shown in columns 2 and 3 of Table 5 and disaggregated by decade in Table 6, likewise reveals few differences arising from the addition of the spatial effects. The conclusion drawn here is that while the data exhibits spatial autocorrelation that is likely a result of unobserved omitted variables, this spatial autocorrelation is not causing incorrect inference to be made about the covariate's effects on homicide rates. The lack of substantive differences in the outcomes of the spatial models versus the non-spatial models should not be seen as an indication that the spatial models were unsuccessful. Rather, the recognition that homicide rates may display spatial autocorrelation, a fact that was shown to be true, necessitates that the pattern and effects of the clustering be fully explored. That the spatial model exhibits similar coefficient estimates to the original model in the presence of the spatial autocorrelation lends additional credence to the results obtained.[16]

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[15] In fact, the spatial diagnostics reported in Table 3 reveal that a spatial lag specification may be appropriate in 1970 and 1980; however, the spatial error specification is the "preferred" alternative, based on the significance tests. The model fit statistics from a spatial lag specification for these two years likewise suggest that the spatial lag is an inferior alternative to the spatial error. These results are available from the author.

[16] It is also important to note that this analysis has not attempted to uncover or correct for potential spatial heterogeneity in the data, a distinct spatial effect which is often difficult to differentiate from spatial autocorrelation. Spatial heterogeneity refers to geographic variation in the effect of a covariate on the dependent variable. The

6. Conclusion

This paper shows that immigrant growth and concentration, measured as the change in the proportion of an MA's population that is foreign born, is inversely related to the MA homicide rate in the period 1980-2000, a result consistent with the limited longitudinal macro-level research on the immigration-crime association (Ousey and Kubrin 2009; Stowell et al. 2009). This finding of a negative relationship between immigration change and homicide rate change is especially noteworthy since the cross-sectional association between the two variables is in the opposite direction. The exploratory analysis confirms that the spatial clustering of homicide rates observed by Baller et al. (2001) at the county-level is also present at the MA-level. While part of this MA-level spatial autocorrelation appears to be the result of the clustering of observed explanatory variables, there is evidence that significant spatial autocorrelation remains which is the outcome of the clustering of unobserved factors; there is little evidence that a diffusion process of homicide rates among MAs is an important explanatory element. The results of the FE analyses suggest that the presence of the spatial autocorrelation in homicide rates is neither driving the coefficient estimates of the covariates' effects nor encouraging incorrect inference regarding those effects.

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geographically weighted regression (GWR) procedure outlined by Brunsdon, Fotheringham, and Charlton (1996) may be useful in this respect, however the use of GWR in the analysis of panel data has not been well established.

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Figure 1:
Moran Scatterplots, by Decade

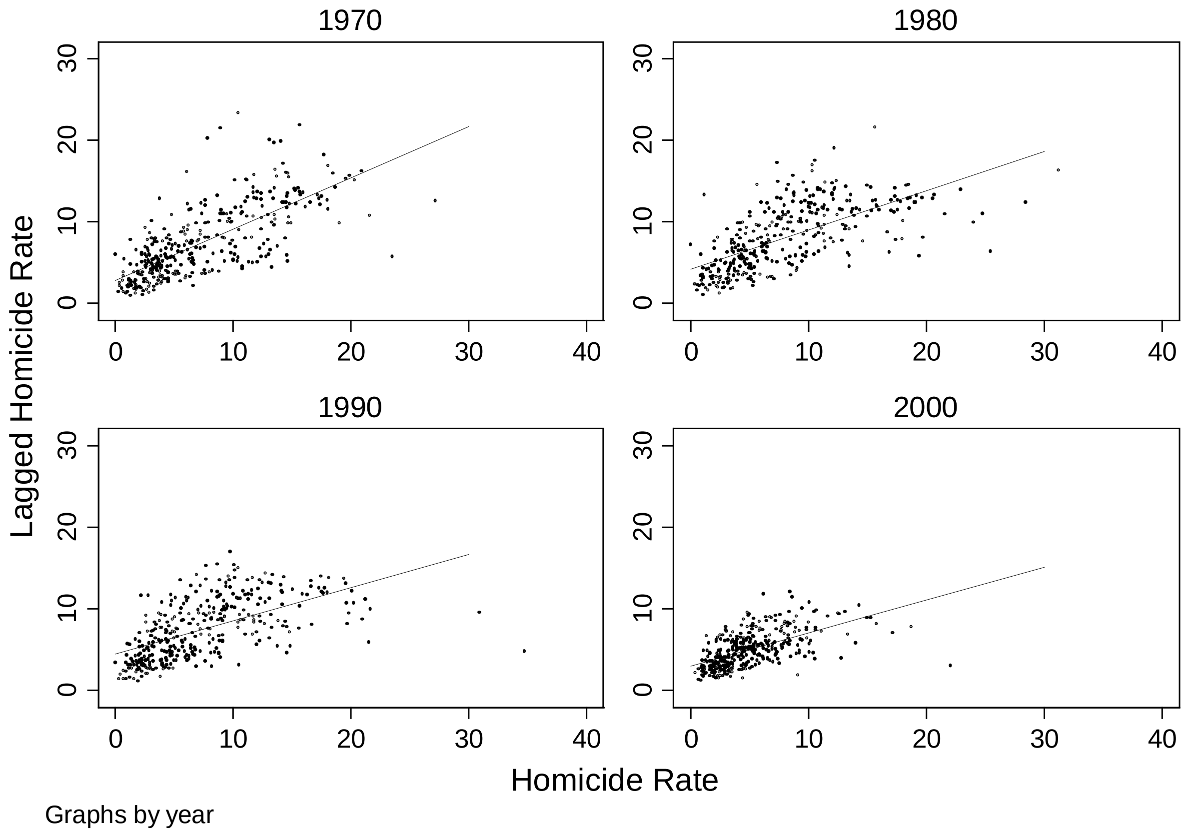
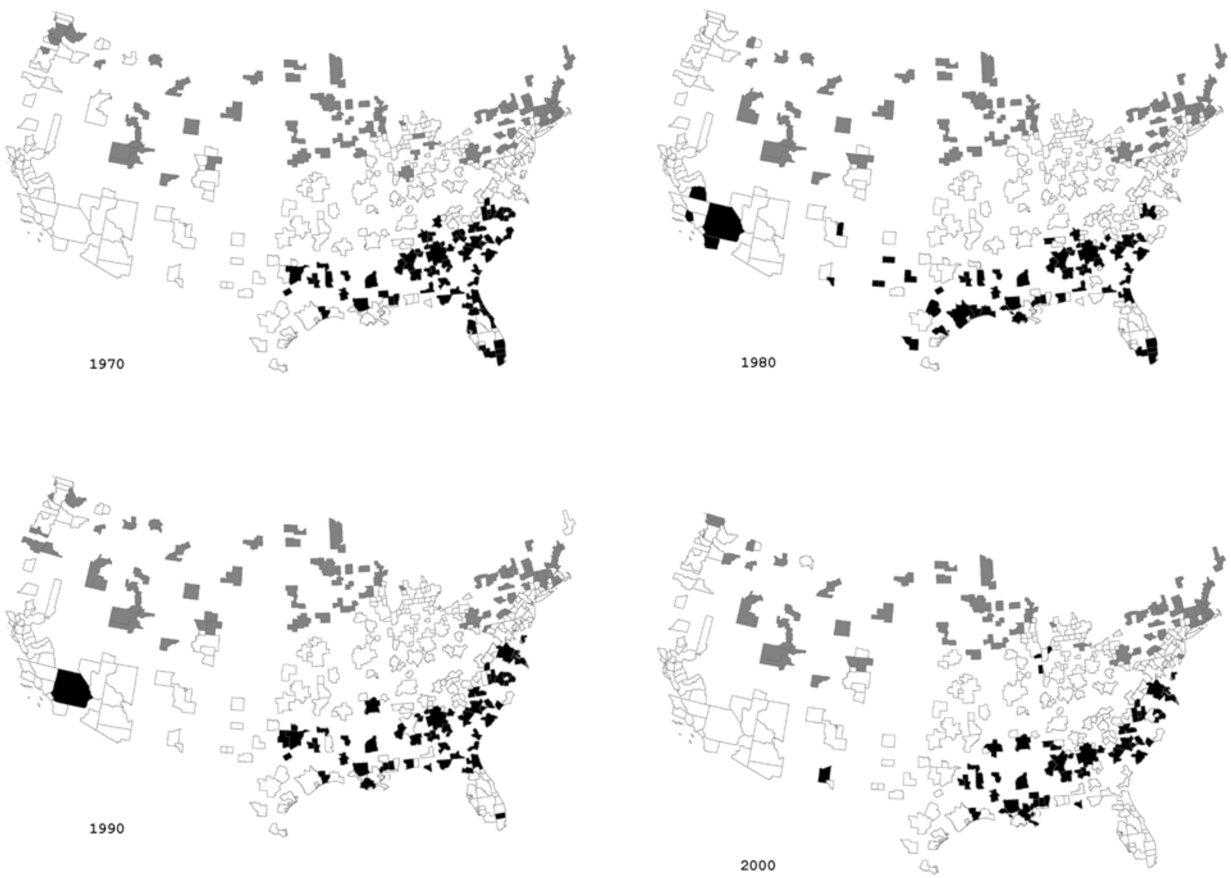


Figure 2:
Local Moran's I Homicide Rate Clusters, by Decade



High-High Clusters ■ Low-Low Clusters ■ No Significant Clustering □

TABLE 1: COEFFICIENTS FROM OLS REGRESSION OF HOMICIDE RATES ON METROPOLITAN AREA STRUCTURAL VARIABLES, BY DECADE

	1970	1980	1990	2000
Foreign Born Index	0.64 *	1.54 ***	0.66 ***	0.06
	(2.42)	*(7.68)*	*(4.33)*	*(0.59)*
Proportion NH Black	0.32 ***	0.26 ***	0.31 ***	0.19 ***
	(12.02)	*(9.79)*	*(14.03)*	*(12.73)*
Economic Disadvantage Index	-0.27	-0.05	0.97 ***	0.67 ***
	(-1.15)	*(-0.21)*	*(5.03)*	*(4.69)*
Adult to Child Ratio	0.12	-0.71	-0.64	-0.31
	(-1.15)	*(-1.55)*	*(-1.70)*	*(-1.07)*
Proportion Male Age 15-24	-0.27 **	-0.34 **	-0.48 ***	-0.12
	(-2.82)	*(-2.83)*	*(-3.77)*	*(-1.22)*
Proportion Divorced	0.83 ***	0.79 ***	0.58 ***	0.27 **
	(3.82)	*(5.16)*	*(4.71)*	*(3.17)*
Gun Prevalence Ratio	0.07 ***	0.09 ***	0.02	0.03 *
	(3.52)	*(5.17)*	*(1.25)*	*(2.35)*
Police per 1,000 Population	1.12 **	2.12 ***	0.89 *	0.58 *
	(2.67)	*(4.67)*	*(2.54)*	*(2.40)*
Population Structure Index	0.09	0.47 *	1.06 ***	0.65 ***
	(0.52)	*(2.38)*	*(5.89)*	*(5.03)*
Northeast Region (Ref)	--	--	--	--
	--	--	--	--
Midwest Region	0.30	0.69	0.25	1.05 **
	(0.53)	*(1.13)*	*(0.46)*	*(2.76)*
South Region	2.97 ***	1.84 *	1.13	0.28
	(4.12)	*(2.50)*	*(1.78)*	*(0.62)*
West Region	0.73	0.31	1.14	1.52 **
	(0.93)	*(0.37)*	*(1.62)*	*(3.05)*
Constant	-2.23	-3.93	1.48	-1.07
	(-1.22)	*(-1.77)*	*(0.67)*	*(-0.62)*
Observations	349	349	349	349
R-squared	0.725	0.717	0.752	0.676
Log Likelihood	-842.18	-863.97	-825.75	-708.18
AIC	1710.4	1753.9	1677.5	1442.4
Schwarz criterion	1760.5	1804.1	1727.6	1492.5

t-statistics in parentheses. *** $p < .001$;.** $p < .01$; * $p < .05$.

TABLE 2: MEAN HOMICIDE RATES, BY REGION

	1970	**1980**	**1990**	**2000**	***# of MAs***
Northeast	3.30	4.16	4.30	2.94	*49*
Midwest	4.45	5.56	5.25	4.30	*85*
South	11.36	11.57	10.66	6.72	*141*
West	5.52	7.41	6.26	4.15	*74*

TABLE 3: SPATIAL DIAGNOSTICS FROM OLS REGRESSION OF HOMICIDE RATES ON METROPOLITAN AREA STRUCTURAL VARIABLES, BY DECADE

	1970		1980		1990		2000	
Moran's I	0.188	***	0.094	***	0.104	***	0.155	***
	(6.69)		*(3.66)*		*(4.01)*		*(5.65)*	
	p-value		*p-value*		*p-value*		*p-value*	
LM Lag	0.000		0.018		0.977		0.069	
LM Lag Robust	0.533		0.606		0.008		0.037	
LM Error	0.000	preferred	0.004	preferred	0.001	preferred	0.000	preferred
LM Error Robust	0.001		0.080		0.000		0.000	

z-scores in parentheses. *** $p < .001$.

TABLE 4: COEFFICIENTS FROM SPATIAL ERROR MAXIMUM LIKELIHOOD ESTIMATION OF HOMICIDE RATES ON METROPOLITAN AREA STRUCTURAL VARIABLES, BY DECADE

	1970	1980	1990	2000
Foreign Born Index	0.23 *(0.79)*	1.33 *** *(6.05)*	0.58 *** *(3.44)*	0.03 *(0.22)*
Proportion NH Black	0.32 *** *(10.65)*	0.26 *** *(9.17)*	0.32 *** *(13.27)*	0.21 *** *(12.36)*
Economic Disadvantage Index	0.08 *(0.33)*	0.15 *(0.59)*	1.16 *** *(5.95)*	0.67 *** *(4.70)*
Adult to Child Ratio	-0.68 *(-1.13)*	-1.02 * *(-2.10)*	-0.68 *(-1.66)*	-0.23 *(-0.76)*
Proportion Male Age 15-24	-0.22 * *(-2.37)*	-0.31 * *(-2.57)*	-0.53 *** *(-4.20)*	-0.17 *(-1.76)*
Proportion Divorced	0.90 *** *(3.96)*	0.80 *** *(4.88)*	0.52 *** *(4.03)*	0.23 * *(2.47)*
Gun Prevalence Ratio	0.05 ** *(2.58)*	0.08 *** *(4.52)*	0.02 *(1.05)*	0.03 * *(2.09)*
Police per 1,000 Population	1.31 ** *(3.24)*	2.11 *** *(4.62)*	0.90 * *(2.50)*	0.60 * *(2.44)*
Population Structure Index	0.18 *(1.02)*	0.54 ** *(2.74)*	1.15 *** *(6.36)*	0.69 *** *(5.36)*
Northeast Region (Ref)	-- --	-- --	-- --	-- --
Midwest Region	0.05 *(0.07)*	0.72 *(0.96)*	0.32 *(0.47)*	1.00 *(1.91)*
South Region	2.63 ** *(3.11)*	1.83 * *(2.24)*	1.01 *(1.41)*	0.22 *(0.41)*
West Region	0.97 *(1.00)*	0.60 *(0.64)*	1.48 *(1.77)*	1.78 ** *(2.80)*
Constant	-0.78 *(-0.44)*	-2.96 *(-1.33)*	2.55 *(1.14)*	-0.44 *(-0.25)*
Lambda	0.43 *** *(6.31)*	0.28 *** *(3.55)*	0.30 *** *(4.00)*	0.40 *** *(5.68)*
Observations	349	349	349	349
R-squared	0.758	0.729	0.764	0.706
Log Likelihood	-826.71	-859.33	-819.93	-696.64
AIC	1679.4	1744.7	1665.9	1419.3
Schwarz criterion	1729.5	1794.8	1716.0	1469.4

z-scores in parentheses. *** $p < .001$;.** $p < .01$; * $p < .05$.

TABLE 5: COEFFICIENTS FROM FIXED EFFECT REGRESSIONS OF HOMICIDE RATES ON METROPOLITAN AREA STRUCTURAL VARIABLES, 1970-2000

	Observed Homicide Rates	Predicted Homicide Rates from OLS Models	Predicted Homicide Rates from Spatial Error Models
Foreign Born Index	-0.53 *	0.12	0.14
	(-2.41)	*(0.91)*	*(1.07)*
Proportion NH Black	0.19 **	0.18 ***	0.20 ***
	(3.22)	*(4.86)*	*(5.64)*
Economic Disadvantage Index	-0.28	0.45 ***	0.50 ***
	(-1.48)	*(3.90)*	*(4.39)*
Adult to Child Ratio	-1.13 *	-0.54	-0.54
	(-2.38)	*(-1.85)*	*(-1.87)*
Proportion Male Age 15-24	0.12	-0.15 *	-0.17 *
	(1.01)	*(-2.08)*	*(-2.37)*
Proportion Divorced	0.07	0.27 ***	0.21 *
	(0.50)	*(3.25)*	*(2.49)*
Gun Prevalence Ratio	0.04 ***	0.09 ***	0.09 ***
	(4.17)	*(15.27)*	*(14.45)*
Police per 1,000 Population	-1.73 ***	-0.27	-0.25
	(-6.13)	*(-1.55)*	*(-1.45)*
Population Structure Index	-1.77 ***	-1.44 ***	-1.41 ***
	(-4.02)	*(-5.32)*	*(-5.26)*
1980	1.98 ***	0.60	0.82 *
	(3.65)	*(1.81)*	*(2.49)*
1990	2.05 *	-0.44	-0.09
	(2.31)	*(-0.81)*	*(-0.17)*
2000	0.36	-2.30 ***	-1.86 **
	(0.31)	*(-3.25)*	*(-2.65)*
Constant	5.98 ***	1.65	2.09 *
	(3.63)	*(1.63)*	*(2.09)*
Observations	1396	1396	1396
Number of MAs	349	349	349

t-statistics in parentheses. *** $p < .001$;.** $p < .01$; * $p < .05$.

TABLE 6: COEFFICIENTS FROM FIXED EFFECT REGRESSIONS OF HOMICIDE RATES ON METROPOLITAN AREA STRUCTURAL VARIABLES, BY DECADE

	Predicted Values from OLS Models			Predicted Values from Spatial Error Models		
	1970-1980	1980-1990	1990-2000	1970-1980	1980-1990	1990-2000
Foreign Born Index	3.88 ***	-0.79 ***	-2.15 ***	3.72 ***	-0.69 **	-2.27 ***
	(18.41)	*(-3.51)*	*(-5.09)*	*(17.78)*	*(-2.93)*	*(-5.28)*
Proportion NH Black	0.15 **	0.47 ***	-0.42 ***	0.16 **	0.50 ***	-0.42 ***
	(2.89)	*(7.42)*	*(-3.68)*	*(3.21)*	*(7.67)*	*(-3.67)*
Economic Disadvantage Index	0.88 ***	-0.39 **	1.28 ***	0.99 ***	-0.25	1.49 ***
	(5.44)	*(-3.14)*	*(3.45)*	*(6.16)*	*(-1.90)*	*(3.93)*
Adult to Child Ratio	-2.06 ***	-1.51 ***	0.05	-2.21 ***	-1.43 ***	-0.25
	(-5.15)	*(-3.96)*	*(0.06)*	*(-5.57)*	*(-3.59)*	*(-0.30)*
Proportion Male Age 15-24	-0.10	-0.10	0.49 **	-0.11	-0.04	0.42 *
	(-1.07)	*(-1.01)*	*(2.55)*	*(-1.20)*	*(-0.41)*	*(2.15)*
Proportion Divorced	0.71 ***	0.18	0.23	0.74 ***	0.16	0.15
	(6.15)	*(1.44)*	*(1.38)*	*(6.43)*	*(1.18)*	*(0.89)*
Gun Prevalence Ratio	0.10 ***	0.07 ***	0.06 ***	0.09 ***	0.06 ***	0.06 ***
	(13.83)	*(11.90)*	*(5.13)*	*(12.68)*	*(10.14)*	*(4.85)*
Police per 1,000 Population	1.17 ***	0.82 ***	-1.15 **	1.25 ***	0.87 ***	-1.19 **
	(5.14)	*(3.66)*	*(-2.91)*	*(5.55)*	*(3.72)*	*(-2.96)*
Population Structure Index	-2.00 ***	-1.79 ***	0.60	-2.19 ***	-1.56 **	0.90
	(-4.68)	*(-4.03)*	*(0.67)*	*(-5.17)*	*(-3.37)*	*(0.98)*
1970	--			--		
	--			--		
1980	-0.58	--		-0.43	--	
	(-1.29)	--		*(-0.96)*	--	
1990		-0.97 *	--		-0.77	--
		(-2.40)	--		*(-1.85)*	--
2000			-0.19			0.10
			(-0.39)			*(0.20)*
Constant	1.60	2.07	4.28	1.98	1.50	6.74 *
	(1.21)	*(1.28)*	*(1.41)*	*(1.51)*	*(0.89)*	*(2.01)*
Observations	698	698	698	698	698	698
Number of MAs	349	349	349	349	349	349

t-statistics in parentheses. *** *p* < .001;.** *p* < .01; * *p* < .05.

TABLE 7: COEFFICIENTS USING ALTERNATIVE WEIGHT MATRICES FOR FIXED EFFECT REGRESSIONS OF HOMICIDE RATES ON METROPOLITAN AREA STRUCTURAL VARIABLES, BY DECADE

	Predicted Homicide Rates from Spatial Error Models: 2nd Order Rook Contiguity Weight			Predicted Homicide Rates from Spatial Error Models: Distance Threshold Weight		
	1970-1980	**1980-1990**	**1990-2000**	**1970-1980**	**1980-1990**	**1990-2000**
Foreign Born Index	3.12 ***	-0.34	-2.28 ***	3.31 ***	-0.60 **	-2.12 ***
	(17.67)	*(-1.64)*	*(-5.40)*	*(18.90*	*(-2.74)*	*(-5.15)*
Proportion NH Black	0.26 ***	0.46 ***	-0.42 ***	0.23 ***	0.48 ***	-0.41 ***
	(5.96)	*(7.97)*	*(-3.70)*	*(5.29)*	*(7.93)*	*(-3.74)*
Economic Disadvantage Index	0.36 **	-0.11	1.50 ***	0.53 ***	-0.28 *	1.47 ***
	(2.63)	*(-0.94)*	*(4.05)*	*(3.93)*	*(-2.32)*	*(4.06)*
Adult to Child Ratio	-1.76 ***	-1.15 ***	-0.22	-1.96 ***	-1.30 ***	-0.03
	(-5.27)	*(-3.31)*	*(-0.26)*	*(-5.91)*	*(-3.56)*	*(-0.04)*
Proportion Male Age 15-24	0.09	0.00	0.40 *	0.02	-0.10	0.37 *
	(1.17)	*(0.05)*	*(2.06)*	*(0.23)*	*(-1.10)*	*(1.98)*
Proportion Divorced	0.54 ***	0.28 *	0.17	0.59 ***	0.19	0.24
	(5.60)	*(2.39)*	*(1.04)*	*(6.17)*	*(1.56)*	*(1.46)*
Gun Prevalence Ratio	0.07 ***	0.06 ***	0.06 ***	0.08 ***	0.06 ***	0.06 ***
	(11.65)	*(11.10)*	*(5.15)*	*(13.17)*	*(11.52)*	*(5.28)*
Police per 1,000 Population	1.37 ***	0.80 ***	-1.14 **	1.06 ***	0.86 ***	-1.19 **
	(7.24)	*(3.89)*	*(-2.90)*	*(5.64)*	*(4.00)*	*(-3.11)*
Population Structure Index	-1.21 ***	-0.77	0.78	-0.52	-1.41 ***	0.85
	(-3.38)	*(-1.90)*	*(0.87)*	*(-1.47)*	*(-3.30)*	*(0.97)*
1970	--			--		
	--			--		
1980	-0.78 *	--		-0.64	--	
	(-2.06)	--		*(-1.70)*	--	
1990		-1.10 **	--		-1.05 **	--
		(-2.99)	--		*(-2.71)*	--
2000			0.08			-0.13
			(0.17)			*(-0.27)*
Constant	0.76	0.26	6.28 *	1.68	1.58	5.39
	(0.69)	*(0.18)*	*(2.08)*	*(1.54)*	*(1.02)*	*(1.83)*
Observations	698	698	698	698	698	698
Number of MAs	349	349	349	349	349	349

t-statistics in parentheses. *** $p < .001$;.** $p < .01$; * $p < .05$.