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12 June 2014

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Abstract

This paper investigates spatial diffusion patterns of high levels of violence across Mexican municipalities to nearby locations while also exploring the possible effect of increasing law enforcement resources in some regions of the country. Our approach consists of providing a framework based on spatial regime models to address spatial heterogeneity that indicates instability in the structural determinants of homicides. In this context, a distinction is made in relation to the regimes that are analyzed between those municipalities that were exposed to joint operations ('operativos conjuntos') and those that were not exposed to the operations. Spatial econometric models were estimated for each regime in light of investigating possible spillover effects arising from the covariates. The results point to differences in regard to the significance, magnitude, and sign of the effects related to some variables according to each spatial regime's specification. While the direct effects show that socioeconomic variables tend to play an important role in explaining the variation of homicides in the non-joint operation regime, the historical level of homicides and closeness to the U.S. border operate in a more significant way for those municipalities in the joint operation regime. In regard to the indirect effects estimates, a positive and significant spillover effect upon homicide rates is attributed to our law enforcement variable as well as to the proxy variable of informality. These spillover effects are found to be greater in magnitude especially in those municipalities exposed to joint operations.

Keywords: ESDA, spillover effects, homicides, spatial regime model

1. INTRODUCTION

In recent years Mexico has experienced increasing levels of violence, which have been attributed to the war among drug cartels, especially after the deployment of federal armed forces to combat the organizations belonging to drug cartels. Even though army interventions have taken place since the beginning of 2007 in different municipalities in order to bring down organized crime, homicides seem to have spread out to other municipalities, sparking a debate on whether other localities now suffer from the same problems due to the movement of criminal activities. The spatial displacement of criminal activity in Mexico makes an interesting case study since most studies have focused on developed countries.

According to Clarke and Weisburd (1994), there is a diffusion effect of crime when an intervention to reduce crime has occurred in a place and in addition there are reduction benefits in places close to that area that were not targeted for intervention. In contrast, spatial displacement of crime refers to the relocation of such activity from one place to another as the result of an intervention. Even though displacement is seen as the opposite of diffusion, some still see benefits, for example Guerette and Bowers (1999) mention that the total volume of crime could be less than before the intervention and also that the type of crime displaced may be less serious. Barr and Pease (1990) mention negative effects of displacement, such as the concentration of crime, the focusing of crime on more vulnerable groups, or its relocation to areas where it has more impact.

Moreover, some authors, such as Cohen and Tita (1999), use the term diffusion in the sense of displacement. These authors analyzed the spatial spread effect of homicides in neighboring areas in Pittsburgh; using dynamic Exploratory Spatial Data Analysis (ESDA), they distinguish between hierarchical diffusion (between common influences) and contagious diffusion (between adjacent units). They find contagious effects whenever there are peaks of total homicides.

Ratcliffe (2010) finds that usual methods are more relevant when used together with spatial tools such as the Global Moran's I and the Local Indicator of Spatial Autocorrelation (LISA) and that, when applied to crime measures in neighborhoods of Philadelphia, stronger results are produced by using the combination of methods. In other cases, the use of exogenous events as natural experiments has been useful for the analysis of dispersion. For example, Di Tella and Schargrodsky (2004) use the terrorist attack on a Jewish center in Buenos Aires as a focus to identify geographical units for police involvement, finding a lowering effect on crime, measured as car robbery, only in the same area of the attack, but no effect outside that small geographical unit. The authors acknowledge that such a method does not allow measurement of the magnitude of crime displacement to other areas.

The effects of geographical movements of crime have been reviewed in other studies. The conclusions of Bannister (1991), Eck (1990), and Hessenling (1994), among others, can be summarized as similar: even though the phenomenon exists, it is not an unavoidable effect, and when it occurs it is limited in size and magnitude. They all agree that if there are other factors affecting crime, then displacement may be the result of a combination of factors, making it more difficult to discern the real displacement since other types of crime may also be on the rise.

Understanding both concepts is crucial given the current context from which this study arises: a) the fight between different drug cartels to control geographical areas and b) the joint military operations (Operativos Conjuntos Militares) that started in 2007 (technically at the end of 2006), when the federal government incremented the presence of the army in those areas.[1] The question of to what extent such interventions have contributed to the increase in homicides experienced, rather than to pacification, since these incidents occurred has attracted a great deal of attention, mostly in the media rather than in academia. Hence there is a need for a formal analysis to have a better understanding of the violence and what exactly is happening. As Escalante (2009) notes, there is no general explanation for territorial increases of violence, leaving a door open for research on the spatial analysis of the problem in Mexico

In this sense, we aim to investigate spatial diffusion patterns of high levels of violence to nearby locations while also exploring the possible effect of increasing law enforcement resources in some regions of the country. Our approach consists of modeling the spatial process associated with the increase in homicides in Mexican municipalities by using exploratory spatial data analysis (ESDA) techniques along with spatial econometric methods. The main contribution consists of developing a framework based on spatial regime models to address spatial heterogeneity that could indicate the possibility of instability in the structural determinants of homicides. To date, and to the best of our knowledge, there is no other study that explicitly addresses the presence of spatial regimes using crime data in a cross-sectional setting for Mexico.

The paper is structured as follows: section two outlines the context of increasing violence in Mexican regions and presents preliminary evidence for motivating the use of spatial regimes; section three introduces the spatial methods to be used in the analysis, along with the description of the database. The fourth section presents the results for the spatial analysis and the direct and indirect effects for diffusion. Finally, some conclusions are drawn.

[1] These operations were coordinated by military and federal police corporations and were backed by state and local security forces. The strategy included the dismantling of criminal organizations, the arrest of the largest possible number of criminals and confiscation of drug shipments, and, in particular, the deployment of military operations in several regions of the country and a permanent increase in resources devoted to military forces.

2. CONTEXT AND MOTIVATION FOR SPATIAL REGIMES

The context in which the rising violence in Mexico has taken place can be framed with reference to past violence trends as well as to policies that the government has implemented during previous decades. Most of the discussion about crime and policies has taken place in the public arena and not in academia. Perhaps because of this, and as Escalante (2010) notes, there is little knowledge in Mexico about crime as a social problem, since social scientists have analyzed different topics. Escalante (2010) also argues that the territorial distribution of crime suggests a diverse profile of crime, making heterogeneity a rule, but no general pattern can explain such a rise in violence.

A policy view to explain the rise in crime and the army interventions in the different states in Mexico can be found in the study of Chabat (2010). This author states that drug cartels were not a problem for the government up to the mid 1980s, when Mexico became an important route for trafficking drugs to the U.S.; in addition, Mexico had weak institutions, a lack of containment of corruption, and a really appalling tolerance policy toward the cartels. Chabat also suggests that there was a worsening of the security situation in the second half of the 1990s, possibly due to the economic crisis and the recruitment of some previous ex-armed forces by some cartels.

In a complementary explanation, Escalante (2009) presents a trend for standardized homicides in Mexico over time, which shows a decreasing pattern in the decade of the 2000s, with a slight increase in 2006-2007, but a higher increase in some urban areas. He argues that in the 1990s there were unusual episodes of targeted crime (between some cartel’s heads); these episodes, however, made the population feel insecure, especially in the second half of the decade, and they were accompanied by an increase in violence in northern urban areas, which was previously based in rural areas.

This made the phenomenon more visible; as a result of this, public opinion created pressure for interventions to decrease such episodes.

Chabat (2010) also focuses on the institutional framework for fighting corruption and violence. Although some reforms were implemented, they did not translate into a reduction of corruption levels, and also the U.S. put pressure on the Mexican government to fight the cartels' activities. In his analysis, as in that of others (Sanchez, 2011; Maldonado, 2012), the constant is the permeating of the structure of the institutions, such as the army and local police, by the cartels. In addition, these authors suggest that this was a factor determining the army intervention in some states in 2007 and 2008, in addition to an urgency to legitimate a politically debilitated presidency after the 2006 elections. Other factors were also present: the cartels started to fight for specific areas to control; the formerly reluctant governments began to fight violence; there were conflicts with the U.S. Government due to drug policy related issues; and there was an increasing demand for drugs within Mexico (Chabat, 2010).

As Escalante (2010) also notes, the spatial heterogeneity of the country needs to be explored when analyzing the rising violence, and this includes linking the homicide trends with social, economic, and demographic factors that are specific to geographical units. In this sense, while investigating the existence of spatial diffusion patterns and some structural variables associated with the increase in homicides in the Mexican municipalities, one must consider two complementary scenarios. On the one hand, there is the fight between different drug cartels to control geographical areas that led to joint military operations (Operativos Conjuntos Militares) between federal and state level governments. The two scenarios share one characteristic: the specific regions where violence occurred. The joint operations took place in seven states: Michoacán, Guerrero, Baja California, Nuevo León, Tamaulipas, Chihuahua, Sinaloa, and Durango, and in these states there has also been a bloody struggle among drug organizations to control the territory (see Figure 1).

[Figure 1 about here]

On the other hand, an additional peculiarity emerges: some of these states have previously been involved in either drug trafficking or illicit drug production, especially near the border with the U.S. (Sanchez, 2011). This issue certainly plays a role in explaining the rise in, and particularly the location of, the violence. As Zimring and Hawkins (1999) hypothesize, “the creation and expansion of illegal markets will produce extra homicides when social circumstances conducive to lethal violence exist.”

In fact, when analyzing the spatial distribution of homicides in previous years, it can be noted that there is a clear concentration of high levels, particularly in most of the areas that are the center of attention today. In Figure 2 there are four maps showing the spatial distribution of homicides in Mexico in 1990, 2000, 2005, and 2010; the last two dates correspond to the period here analyzed. Some patterns emerge in these maps: a) levels of violence are not randomly distributed; instead, similar rates of violence tend to cluster together in space (i.e., violence exhibits positive spatial autocorrelation), b) the presence of positive spatial autocorrelation could indicate evidence of spatial diffusion/contagion across municipalities, particularly during the period 2006-2010 (as shown in Figure 3), and c) the diffusion pattern appears not to have occurred across the whole country but only within particular regions.

[Figure 2 about here]

[Figure 3 about here]

These past and current patterns allow the exploration of different regimes in the spatial distribution of homicides. In light of the results it is plausible to hypothesize that some correlations might suffer from differing effects across these regimes as well. In other words, the question raised in this paper focuses on whether the structural determinants of homicide rates are invariant across the geography of the study. The case in which structural conditions have differing effects on homicide levels in different geographical units leads to what is called spatial regimes (Messner and Anselin, 2004). This situation is formally addressed by considering the presence of spatial heterogeneity when modeling our variable of interest and which coefficients associated with the correlates vary systematically across geographic areas (Baller et al., 2001).

In the next section we describe the methods used to examine the spatial distribution of homicides in Mexican municipalities in a spatial regime approach. We start by exploring the spatial process of homicides through Exploratory Spatial Data Analysis (ESDA), more specifically the Local Indicator of Spatial Autocorrelation (LISA), in order to visualize and locate the extent to which high levels of homicides spread out to neighboring locations. Consequently, the data-generating process is specified and the appropriate modeling strategy described. Finally, a formal specification of the econometric model addressing the direct and indirect effects with spatial regimes is presented.

3. METHODS AND DATA

3.1 ESDA for Detecting Spatial Regimes in the Distribution of Homicides

Spatial regimes are a form of spatial heterogeneity or, in other words, the variable of interest is not stable over space. When that variable is characterized by distinct distributions (e.g., with a different mean or variance) for different geographical units, these subregions might point to the existence of spatial regimes.

We examined the possibility of spatial regimes in homicide rates based on the past and current spatial patterns previously described. The use of Exploratory Spatial

Data Analysis (ESDA) helps to visualize and describe the spatial distribution of homicides, which in turn assists us in the identification of spatial regimes and other kinds of spatial instability. This statistic assesses a null hypothesis of spatial randomness by comparing the values of local pairs, that is, the values of each specific location with the values in neighboring locations (Anselin, 1995). It is particularly useful as it allows the decomposition of spatial association into four categories: when a location with an above average value is surrounded by neighbors whose values are also above average (high-high, HH) or when a location with a below average value is surrounded by neighbors with below average values (low-low, LL). The decomposition of spatial association may also occur when a location with an above average value is surrounded by neighbors with below average values (high-low, HL), and vice versa (low-high, LH); see Anselin (1993) for a detailed description of the statistical properties of LISA statistics.

3.2 Testing for Spatial Regimes

Spatial heterogeneity arises when structural changes related to location exist in the data. In such cases, spatial regimes might be present; they are characterized by differing parameter values or functional forms (e.g., crime in certain regions might be structurally different from crime in other regions). Here, the assumption of a fixed relationship between dependent and independent variables that holds over the complete data set is formally investigated.

A formal assessment for testing the structural stability of the regression coefficients across spatial subsets is possible through the spatial Chow test (Anselin, 1990). A spatial switching regression, or spatial regimes model, applies spatial Chow tests to diagnose structural instability in parameters across regimes. A significant coefficient variable suggests a “level” shift in homicide rates across specific areas of study.

A standard regime model takes the form:

$$\begin{bmatrix} y_i \\ y_j \end{bmatrix} = \begin{pmatrix} X_i & 0 \\ 0 & X_j \end{pmatrix} \begin{bmatrix} \beta_i \\ \beta_j \end{bmatrix} + \begin{bmatrix} \varepsilon_i \\ \varepsilon_j \end{bmatrix} \tag{1}$$

where *i,j* index discrete spatial subsets or regimes of the data and a test of the null hypothesis consists of $\beta_i=\beta_j$, where the β are estimated in the above equation. This is the standard Chow test distributed as an F with (K, $N-2K$) degrees of freedom:

$$C = [(e_R^{'} e_R - e_U^{'} e_U)/K][(e_U^{'} e_U)/(N-2K)] \sim F_{(K,N-2K)} \tag{2}$$

where e_R and e_U are the OLS residuals from a restricted model and from an unrestricted model, respectively; N is the number of observations and K is the number of regressors. However, when the error terms are spatially autocorrelated, the above expression is no longer valid. A corrected version of the test is referred to as a *spatial* Chow test (see Anselin 1998, 1990):

$$C_s = \left[e_R^{'}(I-\lambda W)^{'}(I-\lambda W) e_R - e_U^{'}(I-\lambda W)^{'}(I-\lambda W) e_U \right] / \sigma^2 \sim \chi_K^2 \tag{3}$$

where λ represents the ML estimate for the spatial parameter and σ^2 the estimate for the error variance for either the restricted model (LM test), the unrestricted model (W test), or both (LR test), and finally, I is an identity matrix of dimension *nxn*.

3.3 Data-Generating Process

In modeling homicide rates, the rate in any particular municipalities might be expected to depend upon the rates in neighboring municipalities; the result of a diffusion process of violence and the unseen boundaries between neighboring counties (Baller et al. 2001). To account for such a diffusion mechanism, spatial autoregressive

(SAR) models are proposed for the empirical analysis. These models have different specifications that in some cases incorporate as an additional covariate a spatially lagged dependent variable (Spatial Lag Model), a spatially autoregressive error term (Spatial Error Model), or both in the same regression model (SARAR Model). Other SAR model possibilities include lagging predictor variables instead of response variables. In this case, another term must also appear in the model for the autoregressive parameters of the spatially lagged predictors (WX); this is the so-called Spatial Durbin Model (SDM). These models are explored in the empirical analysis; however, because of restrictions of space, we briefly describe the generating process, with its associated direct and indirect effects for the Spatial Lag Model and SDM in the context of spatial regime models. For further information about cross-sectional setting, the reader is referred to LeSage and Pace (2009), or that of Elhorst (2014) in relation to panel data.

The underlying generating process for the Spatial Lag Model is described as follows:

$$y = \rho W y + X\beta + \varepsilon \tag{4}$$

$$y = (I_n - \rho W)^{-1} X\beta + (I_n - \rho W)^{-1}\varepsilon \tag{5}$$

$$\varepsilon \sim N(0, \sigma^2 I_n) \tag{6}$$

where y denotes an *nxn* vector of the dependent variable (i.e., homicides); W is the spatial weights matrix, which is specified as a row-normalized binary contiguity matrix, with elements w_{ij} = 1 if two spatial neighborhoods share a common border but zero otherwise. In this model, the parameters to be estimated are the usual regression parameters β, σ and the additional parameter ρ corresponding to the lagged dependent variable, also known as the spatial autoregressive coefficient. The error term, ε, is assumed to follow a normal distribution with a mean of 0 and a variance of $\sigma^2 I_n$, where I_n denotes an *nxn* identity matrix.

In the case of the SDM, the data-generating process can be formalized as follows:

$$y = \rho W y + X\beta + WX\theta + \varepsilon \tag{7}$$

$$y = (I_n - \rho W)^{-1} X\beta + (I_n - \rho W)^{-1} WX\theta + (I_n - \rho W)^{-1}\varepsilon \tag{8}$$

$$\varepsilon \sim N(0, \sigma^2 I_n) \tag{9}$$

An implication of these models is that a change in the explanatory variable for a single geographical unit can potentially affect the dependent variable in all other units. In other words, a spatial lag specification of the dependent variable and/or a spatial lag of the covariates allows us to quantify spatial spillovers. Because our main interest is to specify a model accounting for spatial regimes, models (4) and (7) can be specified with, essentially, a dummy variable denoting the regime. This can be interpreted as follows in the case of the spatial lag model:

$$y = \rho W y + x_1\beta_1 + x_1 x_2 \beta_2 + \varepsilon \tag{10}$$

assuming for simplicity that x_1 is a continuous variable and x_2 is the spatial regime dummy variable (i.e., 0,1). The reduced form of this model is:

$$y = (I_n - \rho W)^{-1}(x_1\beta_1 + x_1 x_2 \beta_2) + (I_n - \rho W)^{-1}\varepsilon \tag{11}$$

Note that the partial derivative of y with respect to x_1 takes the following expression:

$$\frac{\partial y}{\partial x_1} = (I_n - \rho W)^{-1}(\beta_1 + x_2\beta_2) \tag{12}$$

Now we have the following expression, depending on the value of x_2:

$$\frac{\partial y}{\partial x_1} = (I_n - \rho W)^{-1}(\beta_1 + \beta_2) \qquad \text{when } x_2\text{=1} \tag{13}$$

$$\frac{\partial y}{\partial x_1} = (I_n - \rho W)^{-1}(\beta_1) \qquad \text{when } x_2\text{=0} \tag{14}$$

The corresponding equation (11) in the case of the SDM is denoted as:

$$y = (I_n - \rho W)^{-1}(x_1\beta_1 + x_1x_2\beta_2) + (I_n - \rho W)^{-1}Wx_1(\theta_1 + x_2\theta_2) + (I_n - \rho W)^{-1}\varepsilon \quad (15)$$

Consequently, the partial derivative of y with respect to x_1 can be expressed as follows:

$$\frac{\partial y}{\partial x_1} = (I_n - \rho W)^{-1}(\beta_1 + x_2\beta_2) + (I_n - \rho W)^{-1}(W\theta_1 + x_2W\theta_2) \quad (16)$$

Hence, expressions (13) and (14) are now of the form:

$$\frac{\partial y}{\partial x_1} = (I_n - \rho W)^{-1}(\beta_1 + \beta_2 + W\theta_1 + W\theta_2) \qquad \text{when } x_2\text{=1} \quad (17)$$

$$\frac{\partial y}{\partial x_1} = (I_n - \rho W)^{-1}(\beta_1 + W\theta_1) \qquad \text{when } x_2\text{=0} \quad (18)$$

The results obtained in (14)-(15) and (17)-(18) convey important implications for the proper interpretation of spatial model estimates. Specifically, they allow us to estimate and separate direct and indirect effects from each covariate in the model. In other words, it is possible to differentiate the direct (within a municipality) impact of an independent variable on the dependent variable from the indirect (to/from neighboring municipalities) impact. The latter is particularly relevant in relation to spillover effects. For example, a change in X at any location will be transmitted to all other locations following the matrix inverse W, even if two locations according to W are unconnected (Vega and Elhorst 2013). Another characteristic is that it also includes feedback effects that arise as a result of impacts passing through neighboring units (e.g., from observation *i* to *j* to k) and back to the unit the change originated from (observation i) (LeSage and Pace 2009, p. 35).

Formally, for each model specification a *nxn* matrix arises from the partial derivatives describe above where the direct effects are calculated from the average of the main diagonal elements (own-partial derivatives), while the cumulative sum off-diagonal elements for each row reflects indirect effects (cross-partial derivatives).

In addition, there is a need to produce estimates of the dispersion, which can be used to calculate the standard deviation of each coefficient. These in turn can be used to construct the usual t-statistics for inference regarding the statistical significance of each coefficient's direct and indirect effect. These would show which variables produce (statistically significant) spatial spillover impacts. For such purposes, the appropriate routines in R-software are used.

3.4 Data and Covariates

The data for homicides come from the vital statistics of the Instituto Nacional de Estadistica y Geografia (INEGI). These data consider all types of homicides (ICD-10: X85-Y09)[2] that occurred in Mexican municipalities during the years 2005-2010. We also explore a database for homicides related to drug rivalry or organized crime released by the Presidencia de la Republica. Starting in 2007, a database on homicides related to organized crime was produced for statistical purposes only; no ministerial or judicial information was included, only the numbers of deaths in municipalities and states. These deaths are classified as homicides related to organized crime if they occur with extreme violence or as an event involving more than two victims and include at least two of the following criteria: an injury resulting from the use of a firearm; torture and severe injuries; a body is found in the interior of a vehicle; materials characteristic of the modus operandi of organized crime are used; and particular facts were related to the death, such as if the event occurred in an ambush or was a persecution or if a message linked to organized crime was found.

However, these data exhibit some issues relating to data-gathering reliability given the criteria used when classifying homicides and because for some of the cases no official death certificate is attached. These factors in turn produce an overestimate of the

[2] International Classification of Diseases, World Health Organization.

total counts of homicides related to organized crime or drug rivalry compared to those officially reported by INEGI (Merino and Gomez 2012). Even though we analyzed both databases currently available in Mexico, the final set of results is based on mortality data from the official vital statistics report by INEGI.[3]

All data come from officially collected databases, and the summary of the variables is presented in Table A1 of the Appendix. We include as a covariate a set of factors that, usually, the literature relates to crime. One of them is the previous level of homicide rates in each municipality, measured as the average during a five-year period before the deployment of armed forces to particular states in Mexico, in order to include the trend in crime at the local level.

The rate of youth unemployment is one variable that may be a determinant in the increase in homicides if we consider that a lack of opportunities may make crime attractive. Even though there is no consensus on such an effect, we include this variable as a proxy for opportunities available to the young. The other covariate that is included is the average number of years of schooling in the municipality. Education is considered to be a factor related to crime since more educated individuals are supposed to ponder the actions associated with crime, and then expecting a reduction of the phenomenon.

Inequality may have an incidence on social dissolution and may lower the rewards for individuals on a low income of being involved in legal activities. Here we have used the Gini Index at the municipal level as calculated by the Consejo Nacional de Evaluacion de la Politica de Desarrollo Social (CONEVAL) for 2005.

Heterogeneity of the population and social fragmentation may also affect the rates of homicides and violence. Here we consider the percentage of births without social security registration as a proxy for informality. In Mexico, a worker employed in

[3] Also, Rodriguez-Oreggia and Flores (2012) detect that between 8-12 percent of municipalities have at some points in time more homicides related to narcotics than the total official account of homicides, which is clearly a mistake in the database.

the formal sector of the economy has social security benefits by law, allowing him or her immediate family the use of the public health system. Those in the informal sector are usually not covered in terms of insurance and other benefits. The divorce rate is a measure of family disruption and is commonly positively associated with homicides. This variable is included and standardized per 1,000 inhabitants.

We also include the percentage of the population working in agriculture. This variable proxy is included, on the one hand, to reflect the economic opportunities in the area, since earnings associated with agriculture are usually lower, and, on the other hand, to show how attractive the local market is for drug-related activities. The higher the agricultural activity, the lower the acquisitional power of individuals to market drugs.

Some controls for institutional characteristics of the localities are also considered. We considered data from administrative records reported by INEGI in 2005 at the state level, which illustrates the ratio of sentences issued relative to preliminary investigations. This is a proxy for the administration of justice in each state.

One of the most common criticisms of problem-oriented policing efforts is that crime will simply relocate to other times and places since the “root causes” of crime were not addressed or because offenders may remain on the streets after certain crime opportunities are reduced. This phenomenon has important implications for many problem-oriented policing projects (Gurette 2009). While targeting a particular area with extra police resources might reduce crime in that particular location, criminal activity might just move to places not protected by police intervention. Addressing this effect in our investigation is important given the fact that increases in law enforcement in specific regions are attributed to the joint operations discussed above. We must note that data for a number of police forces at municipal level were not available when this study was being done. Nonetheless, we use as a proxy variable the number of arrests that are drug-related and that are prosecuted by federal law enforcement authorities. It is assumed that there is a positive relationship between the number of arrests and increasing law enforcement efforts in a given municipality.

The distance from each municipality to the closest state capital, whether or not the municipality belongs to the state, is included in the model with the aim of capturing the effect of population density. We prefer to use this variable instead because of the high correlation of population density with other covariates; thus, issues of multicollinearity are ameliorated. Furthermore, most of the socioeconomic variables included in the analysis also tend to be directly related to this variable. Hence, the closer each municipality is to a capital the more it is expected to be positively and directly associated with homicides. We also calculated the distance from each municipality to the U.S. border. Previous studies have found that "municipios" located close to the U.S. border experience differential increases in homicides, gun-related homicides, and crime gun seizures, particularly after 2004 (Dube et al. 2013). Finally, to account for local drug-related activities, we introduce a dummy if a particular municipality has been identified as a port for entry of drugs into the country, as reported by Roda and Burton (2010).

4. RESULTS

4.1 ESDA Results

Table 1 reports the prevalence of municipalities within each local cluster type obtained from the Local Indicator of Spatial Autocorrelation (LISA) on a yearly basis over the period 2005 to 2010. Three main results arise and are described as follows. First, the number of municipalities exhibiting significance levels for any local-neighbor pairs (cluster type) of total homicide rates rose during the period of study from 418 to 548. Second, at the beginning of the period there were approximately 109 municipalities showing a HH cluster type of total homicides, accounting for 4.4 percent of the municipalities. These are municipalities with homicide rate values of above average that are surrounded by neighbors whose values are also above average. Note that the HH cluster type reached its highest levels in 2008, with 7 percent of total municipalities or approximately 174 municipalities being included in this type. This HH cluster type shows a consistent decline after reaching its peak in 2009 and 2010, although its values are still higher than the initial values in 2005.

[Table 1 about here]

The geographic diffusion patterns followed by the HH clusters are also noteworthy. In Figure 4 it is possible to distinguish the states that are subject to joint operations as well as the distribution of the HH cluster from 2005 to 2010. The latter are displayed as centroids circles with a graduated color corresponding to each year. As observed, much of the concentration of high homicide rates at the beginning of the period occurs in the states that will have joint operations later. This in turn supports the argument that the federal government used to deploy armed forces in particular areas within the country that exhibited considerably high levels of violence. Note also that the diffusion of HH clusters does not seem to spread out across the whole country but is centered particularly within those states facing the joint operations.

[Figure 4 about here]

4.2 Spatial Regime Results

In examining the possibility of spatial regimes in homicide rates, the selection of the regimes is supported on visual inspection as well as the ESDA analysis above described. It has been shown that the states that are subject to joint operations have longstanding drug-related activities and a greater proportion of their municipalities characterized by showing higher levels of homicides even before facing the joint operations. In this context, the analysis consists of distinguishing the regimes from those municipalities facing joint operations versus those that were not exposed to the operations.

The spatial Chow test indicates a rejection of the null hypothesis of coefficients' stability, according to the results shown in Table 2. These results are robust to different model specifications discussed previously, although it is only reported the spatial Chow test corresponds to a spatial lag model. Note that the test is estimated via spatial two-stage least squares (S2SLS) given the inclusion of the spatial lag of the dependent variable at the right-hand side of the model; this estimation method allows the construction of a proper instrument for the spatial lag (Anselin 1988; Kelejian and Robinson 1993; Kelejian and Prucha 1998). The results suggest that the assumption of a stable pattern across regions does not hold, and the test of individual coefficients reveals that several of the correlates exhibit significantly different effects in the municipalities with joint operation in comparison with those with no joint operation. The evidence indicates significantly different coefficients in each of the regimes, even after accounting for spatial dependence attributed to the spatial lag of the dependent variable.

[Table 2 about here]

Once the existence of spatial regimes in the spatial variation of homicides has been defined and formally tested, the next step is estimating spatial econometric models in light of investigating possible spillover effects arising from the independent variables. In Table 3 we show the estimated coefficients corresponding to the spatial lag model and the Spatial Durbin Model. Two findings are noted. First, the AIC comparison between both models and for each spatial regime suggests that the Spatial Durbin Model model fits the data better than the spatial lag model. Second, the spatial lag coefficient (ρ) demonstrates that the endogenous interaction relationship accounts for the homicide variation across Mexican municipalities and that the estimates of the spatial lag effect, comparing each regime, are somewhat similar in the spatial lag and spatial Durbin models, even controlling for other explanatory covariates.

[Table 3 about here]

4.3 Estimated Direct and Indirect Effects Results

The final set of results, which describes direct and indirect effects, is based on the SDM and presented in the rest of this section. The selection of the SDM is also consistent given the circumstances that LeSage and Pace (2009) point out and that might be present in our estimates: (1) there is one (or there are more) potentially important variable(s) omitted from the model, (2) this variable is likely to be correlated with the explanatory variables included in the model; and (3) the disturbance process is likely to be spatially dependent.

Another characteristic in favor of the SDM over the Spatial Lag Model is that both the direct effect and the spillover effect of an explanatory variable depend not only on the parameter ρ and W but also on the coefficient estimate θ_k. In other words, the SDM do not posit prior restrictions on the magnitude of both the direct and the indirect effects, and thus the ratio between the indirect and the direct effects may be different for different explanatory variables (Elhorst 2010, p. 22).

The results arising from the estimation of direct and indirect effects are shown in Table 4. We will first compare across regimes the direct effects estimates exhibiting significant levels. In the case of the non-joint operation regime, some of the socioeconomic variables considered here tend to play an important role in explaining the variation in homicides. For example, higher levels of income inequality in a given municipality positively affect homicides rates in such a location. Administration of justice shows a significant and negative expected effect (-0.004) on homicide rates in the non-joint operation regime, although the magnitude of the effect appears to be limited. For the same type of spatial regime, family disruption tends to have a positive direct effect on homicide rates (0.040) as do informality levels, which tend to positively influence homicide rates (0.099). Note that past levels of violence, or historical homicides rates, are found to be significant in both regimes, although the magnitude is greater in the joint operation regime (0.001 and 0.014 respectively). Conversely, the direct effects associated with the law enforcement variable are found to negatively affect homicide rates in a given municipality, and its magnitude is approximately the same in both regimes (-0.109 and 0.094 respectively).

[Table 4 about here]

Interesting results arise from the estimation of indirect effects that, as discussed above, are associated with spillover effects. First, agricultural employment, historical levels of homicides, and distance to the U.S. border exhibit significant indirect effects (spatial spillovers) in both regimes, but the estimates are approximately three times higher in magnitude in the joint operations regime (-0.230, 0.016, and -0.514 respectively).

Conversely, the indirect effects of income inequality, administration of justice, and port of entry or exit for drug trafficking are statistically significantly different at 99 percent level only in the non-joint operation regime, while exhibiting the expected effect (0.398, -0.219, and 1.062 respectively). These results suggest evidence of a cumulative impact of higher levels of income inequality associated with increases in homicides rates across neighboring geographic units in the sample. More interesting is the fact that administration of justice negatively affects homicides rates while generating a negative spillover effect, and where its magnitude seems to overcome the estimated direct effect. The final, but no less important, result is that being proximate to a port of entry or exit for drug trafficking is associated with a spillover effect of higher levels of homicide rates across the region. While the magnitude of the effect is particularly high among all other estimated coefficients with significance levels, this result holds for the non-joint operation regime exclusively. The proxy variable for informality, births without social security, also shows significance at the 99 percent level solely for the joint operation regime and its positive coefficient (0.608), suggesting that increases in informality conditions would be associated with a spillover effect across the region that would in turn positively affect homicide rates.

A significant result that arises concerns positive spillover effects from the law enforcement variable that is roughly equal in magnitude in both regimes. This suggests that increasing law enforcement in a particular region would experience a feedback effect across regions (municipalities) that would eventually positively impact homicides at the original location. In other words, the results suggest that boosting a particular area with law enforcement personnel would bring down the number of homicides in that particular area as the direct effects show negative and significant coefficient in either of the regimes (0.333 and 0.349); however, the positive spillover across the rest of the regions appears to be significantly higher in magnitude, leading to a positive cumulative effect on homicides. This effect seems to be consistent with the argument that crime displacement occurred particularly after the deployment of armed forces in specific areas of Mexico.

5. CONCLUSION

In this paper we have aimed to analyze the extent of the diffusion of crime, measured with homicides, between the Mexican municipalities from 2005 to 2010. During this period, Mexico was characterized by a rise in organized crime, and while some army intervention was executed in some states, crime seems also to have increased in other nearby localities. Here we look at this particular phenomenon by using ESDA techniques and exploring the existence of spatial regimes in the variation of homicide rates across municipalities. In doing so, we try to link some other local factors with a set of covariates. For a developing country immersed in an organized crime wave, the analysis and implications are relevant, not only for Mexico but for similar countries in the region.

The LISA analysis suggests an increase in clusters of homicides for the period of consideration in 2 percentage points of the municipalities. Spatial clustering of high levels of homicides is found to occur in the first years under analysis, particularly in states where army intervention took place later. Even after the army intervention, most of them remained high-high clusters of violence. The evidence also points to a diffusion of high levels of homicide rates to nearby municipalities.

Given past and recent spatial variation trends of homicide rates across municipalities, we allow for the possibility of spatial regimes. In formally evaluating this, we found two spatial regimes corresponding approximately to the states that were exposed to the joint operation versus those that were not. Consequently, we estimated spatial econometric models that corresponded to each regime aimed to account for spatial dependence among the observations. A Spatial Durbin Model appeared to be the appropriate specification when estimating the effect of socioeconomic, law enforcement, and drug-related activities variables upon homicide rates. Most important is the possibility of capturing spillover effects associated with these variables, given the estimation of direct and indirect effects.

The spatial regression results point to differences in regard to the significance, magnitude, and sign of the effects related with some variables according to each spatial regime's specification. While the direct effects show that socioeconomic variables tend to play an important role in explaining the variation of homicides in the non-joint operation regime, a historical level of homicides and closeness to the U.S. border operate in a greater way for those municipalities in the joint operation regime. In regard to the indirect effects estimates, a positive and significant spillover effect upon homicide rates is attributed to our law enforcement variable as well as to the proxy of informality. These spillover effects are found to be greater in magnitude especially in those municipalities exposed to joint operations.

The implications of this analysis are important. Provided that the only significant intervention to fight organized crime was army intervention in some areas, the results suggest that such actions were mostly ineffective in spatially restraining levels of violence, at least during the period considered here, leading to the spread of organized crime to neighboring areas. This calls for the implementation of other actions, either to replace this or to be complementary to it, in places where homicides have increased and spread among areas.

Two final comments should be given careful attention. First, we recognize that this is a very sensitive topic that could be approached from different fields such as civil rights, criminology, the economics of crime, and sociology, among others. No further considerations are implied about whether the federal government acted somehow unilaterally when it developed the "operativos conjuntos" strategy. We recognize that ensuring civilians' right to safety should be fully met by a government under any circumstances.

The second has to do with the theoretical framework and statistical techniques described here. As explained above, these explicitly consider the spatial dependence of homicides where the goal was to show the existence of a spatial diffusion of high levels along with geographic displacement to areas immediately surrounding the direct focus of the policy efforts described. Nonetheless, the inference made from the empirical analysis does not imply a formal causality test between army intervention and rising homicides in absolute terms; other factors such as clashes between drug cartels or groups within them could be influential factors.

Further analysis is required to provide more insights into the cause and effects of particular events relating to rising violence levels in Mexico. In this sense, recently proposed spatio-temporal interaction models that could be applied to crimes events offer great promise for proactive and predictive policing and have the potential to facilitate interventions in existing crime hot spots as well as anticipatory interventions in the forecasted locations of future crime hot spots (Rey, Mack, and Koschinsky 2012).

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Figure 1

States with army intervention as part of the "Operativo Conjunto"

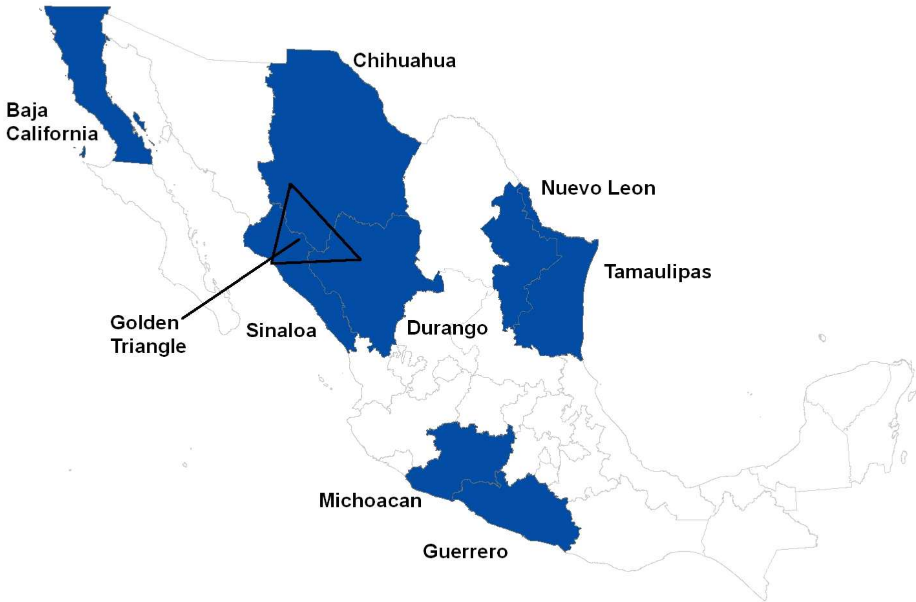

Figure 2. Spatial Distribution of Homicide Rates 1990, 1995, 2000 and 2005

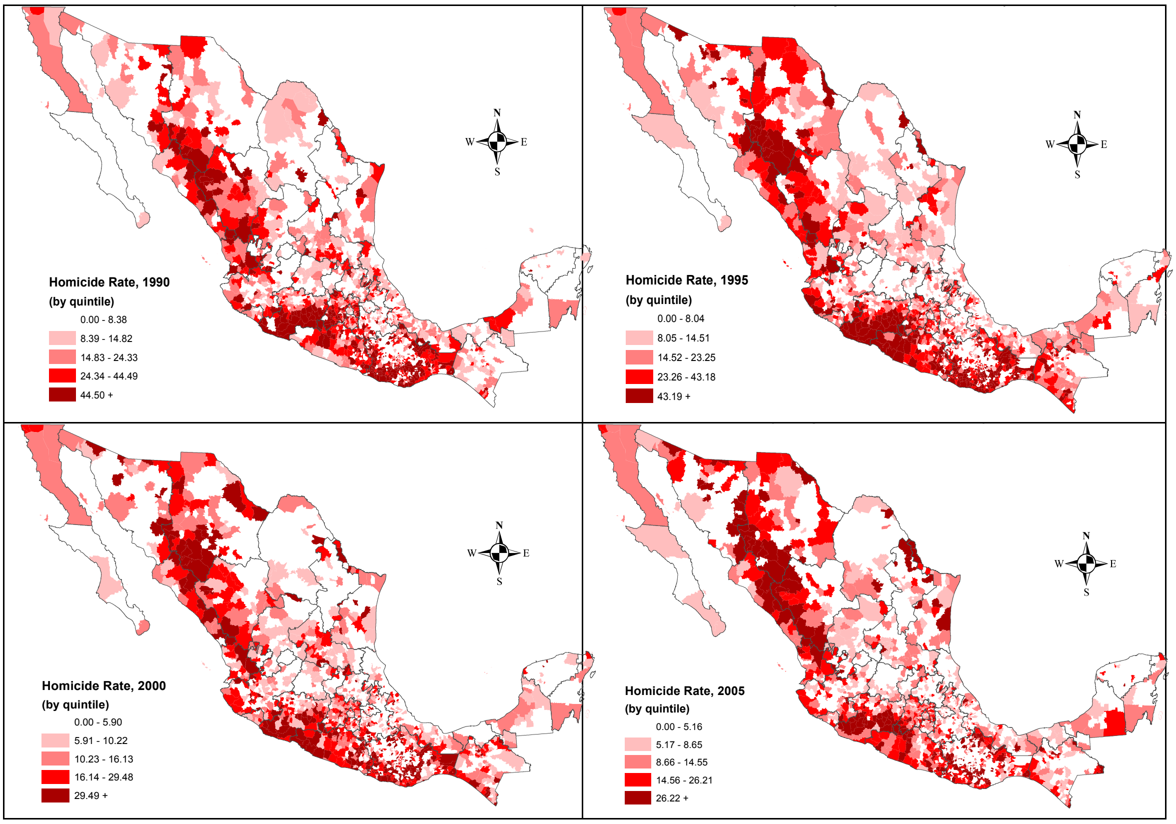

Figure 3

Homicide Rates in Mexican Municipalities, 2010
(Rate per 100,000 inhabitants)

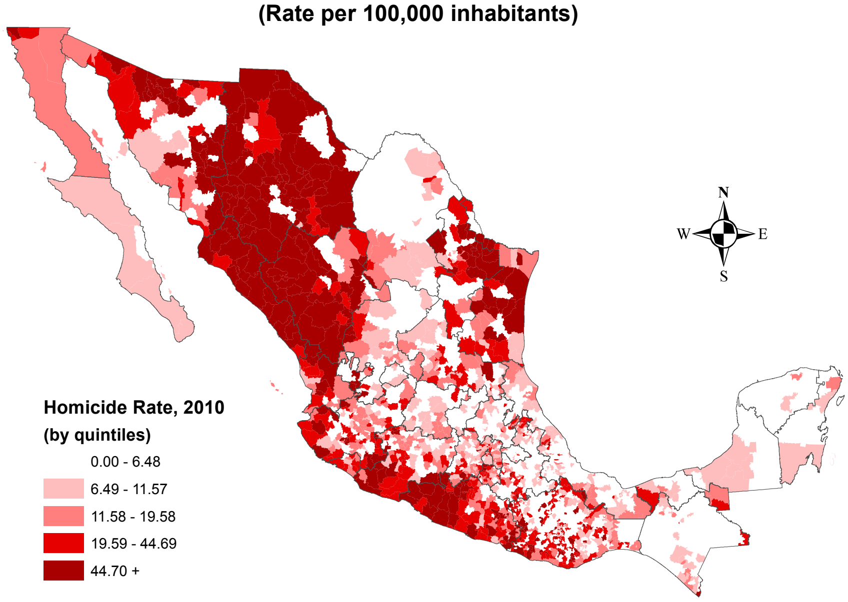

Figure 4. Spatial Diffusion of High-High LISA Clusters of Homicides Rates, 2005-2010

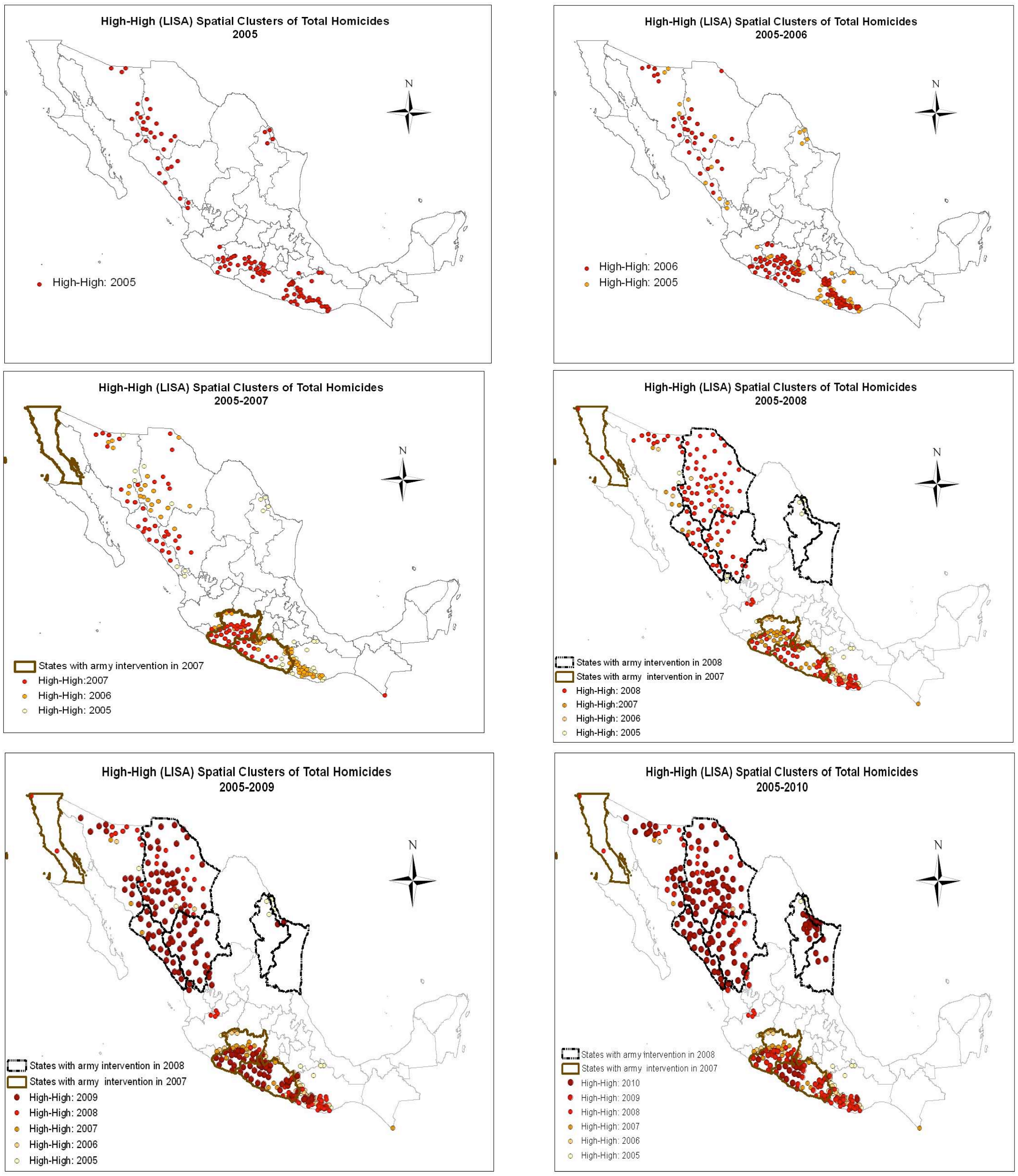

Table 1. Percentage of municipalities with significant LISA values

Cluster Type	2005	2006	2007	2008	2009	2010
HH (High-High)	4.44	4.97	3.42	7.09	6.32	5.58
	(109)	(122)	(84)	(174)	(155)	(137)
LL (Low-Low)	8.64	10.47	9.21	10.92	10.47	14.87
	(212)	(257)	(226)	(268)	(257)	(365)
LH (Low-High)	2.57	2.04	2.53	2.24	1.96	1.43
	(63)	(50)	(62)	(55)	(48)	(35)
HL (High-Low)	1.39	1.18	1.51	1.26	0.86	0.45
	(34)	(29)	(37)	(31)	(21)	(11)
No Significant	82.97	81.34	83.3	78.48	80.4	77.67
	(2036)	(1996)	(2045)	(1926)	(1973)	(1906)
N	2454	2454	2454	2454	2454	2454

Table 2. Spatial Chow Test Results

	Spatial Lag Model (S2SLS)		
	No Joint Operation	Joint Operation	Structural differences in correlates
Gini Index, 2000	0.245***	-0.231	1.278
	(0.0789)	(0.4144)	
Schooling Years, 2000	-0.018	-0.079	0.196
	(0.0306)	(0.1335)	
% Agricultural Employment, 2000	0.004	0.036	0.529
	(0.0136)	(0.0482)	
Administration of Justice, 2005	-0.007	-0.111	0.583
	(0.0255)	(0.1330)	
Youth Unemployment, 2000	0.001	-0.059	1.2
	(0.0138)	(0.0535)	
% Births without SS, 2005	0.039	0.034	0.001
	(0.0270)	(0.1333)	
% Interstate Migrants, 2005	-0.005	0.011	0.085
	(0.0088)	(0.0400)	
% Divorced	0.007	0.168**	3.048
	(0.0175)	(0.0904)	
Av. Homicides, 2000-2004	0.001***	0.011***	16.828***
	(0.0003)	(0.0024)	
Port	0.359**	-0.166	3.124*
	(0.1722)	(0.2426)	
Arrests Narcotics Per Capita	-0.107***	0.153**	6.826***
	(0.0412)	(0.0709)	
Distance to U.S. Border	-0.074**	0.016	1.104
	(0.0347)	(0.0800)	
Distance nearest Capital	0.009	-0.081	0.666
	(0.0274)	(0.0960)	
Intercept	0.453***	-0.528	1.214
	(0.1748)	(0.8737)	
Spatial Lag Parameter (ρ)	0.717***	0.646***	8.439***
	(0.1138)	(0.1151)	
Global test			39.177***

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 3. Estimated Coefficients from Spatial Regression Models

	Spatial Lag Model		Spatial Durbin Model	
	No Joint Operation	Joint Operation	No Joint Operation	Joint Operation
Gini Index, 2000	0.340 ***	-0.380	0.281 ***	-0.621 *
	(0.0822)	(0.2545)	(0.1057)	(0.3051)
Schooling Years, 2000	-0.006	-0.070	-0.023	-0.111
	(0.0328)	(0.0818)	(0.0356)	(0.0850)
% Agricultural Employment, 2000	-0.008	0.076 **	0.013	0.112 ***
	(0.0152)	(0.0316)	(0.0210)	(0.0387)
Administration of Justice, 2005	-0.086 ***	0.006	0.008	-0.181
	(0.0219)	(0.0797)	(0.0490)	(0.1334)
Youth Unemployment, 2000	-0.008	-0.037	-0.009	-0.041
	(0.0159)	(0.0366)	(0.0167)	(0.0365)
% Births without SS, 2005	0.037	-0.019	0.102 ***	-0.228 **
	(0.0263)	(0.0605)	(0.0337)	(0.0940)
% Interstate Migrants, 2005	-0.019 **	-0.042	-0.015	-0.003
	(0.0095)	(0.0255)	(0.0121)	(0.0295)
% Divorced	0.047 ***	0.108 **	0.038 *	0.023
	(0.0174)	(0.0427)	(0.0191)	(0.0479)
Av. Homicides, 2000-2004	0.002 ***	0.015 ***	0.002 ***	0.013 ***
	(0.0004)	(0.0013)	(0.0004)	(0.0017)
Arrests Narcotics Per Capita	0.065 **	0.120 ***	-0.134 ***	-0.116 ***
	(0.0290)	(0.0261)	(0.04260)	(0.0393)
Port	0.154	0.181	0.098	0.076
	(0.1233)	(0.1239)	(0.12415)	(0.1245)
Distance to U.S. Border	-0.039	-0.085 **	0.029	0.269
	(0.0313)	(0.0407)	(0.0596)	(0.0875)
Distance nearest Capital	0.112 ***	0.061 ***	-0.004	-0.030
	(0.0249)	(0.0224)	(0.04103)	(0.0385)
Intercept	0.124	-0.348 ***	0.155	-0.536 ***
	(0.0933)	(0.0551)	(0.1221)	(0.0630)
W Av. Homicides, 2000-2004			0.000	0.007 **
			(0.0005)	(0.0029)
W Gini Index, 2000			0.101	0.721
			(0.1587)	(0.5151)
W Schooling Years, 2000			0.014	0.059
			(0.0617)	(0.1815)
W % Agricultural Employment, 2000			-0.049	-0.196 ***
			(0.0298)	(0.0666)
W Administration of Justice, 2005			-0.130 **	0.279
			(0.0565)	(0.1683)
W Youth Unemployment, 2000			-0.027	-0.292 ***
			(0.0317)	(0.0813)
W % Births without SS, 2005			-0.073	0.494 ***
			(0.0517)	(0.1312)
W % Interstate Migrants, 2005			-0.008	-0.155 ***
			(0.0176)	(0.0508)
W % Divorced			0.002	0.229 ***
			(0.0332)	(0.0899)
W Port			0.566	0.278
			(0.2347)	(0.2427)
W Arrests Narcotics Per Capita			0.315 ***	0.337 ***
			(0.0522)	(0.0476)
W Distance to U.S. Border			-0.101	-0.444 ***
			(0.0743)	(0.1129)
W Distance nearest Capital			0.157 ***	0.107 **
			(0.0502)	(0.0457)
pho	0.413**	0.491**	0.349***	0.456***
	(0.0243)	(0.0229)	(0.0263)	(0.0238)
N	2039	417	2039	417
Wald	458.76	289.16	365.46	175.72
LR test	387.13	256.52	315.57	161.41
AIC	3402.4	3266.2	3357.7	3169.1
Log likelihood	-1685.177	-1617.109	-1649.834	-1555.527

W denotes the spatial lag of the respective variable. * p<0.10, **p<0.05, ***p<0.01

Table 4. Estimated Direct, Indirect and Total Effects

	Spatial Durbin Model					
	No Joint Operation			Joint Operation		
	Direct	Indirect	Total	Direct	Indirect	Total
Gini Index, 2000	0.303***	0.398***	0.701***	-0.586*	0.739	0.153*
	(2.987)	(1.698)	(2.993)	(-1.986)	(1.017)	(0.181)
Schooling Years, 2000	-0.022	0.006	-0.016	-0.109	0.029	-0.079
	(-0.671)	(0.052)	(-0.168)	(-1.305)	(0.091)	(-0.311)
% Agricultural Employment, 2000	0.008	-0.075*	-0.066	0.100***	-0.230***	-0.129
	(0.421)	(-1.723)	(-1.567)	(1.767)	(-1.604)	(-1.518)
Administration of Justice, 2005	-0.004**	-0.219***	-0.223***	-0.165	0.316	0.150
	(-0.076)	(-3.329)	(-4.608)	(-1.267)	(1.623)	(1.014)
Youth Unemployment, 2000	-0.011	-0.053	-0.064	-0.062	-0.449	-0.511
	(-0.659)	(-1.012)	(-1.140)	(-1.680)	(-3.903)	(-4.094)
% Births without SS, 2005	0.099***	-0.046	0.052	-0.199**	0.608***	0.409***
	(3.041)	(-0.568)	(0.667)	(-2.227)	(3.857)	(3.009)
% Interstate Migrants, 2005	-0.016	-0.026	-0.042	-0.014	-0.229	-0.243
	(-1.391)	(-1.014)	(-1.624)	(-0.516)	(-3.394)	(-3.518)
% Divorced	0.040**	0.034	0.074	0.039	0.347	0.387
	(2.156)	(0.639)	(1.298)	(0.786)	(2.755)	(2.856)
Distance nearest Capital	0.010	0.270***	0.281***	-0.023	0.141	0.118
	(0.247)	(4.237)	(4.916)	(-0.653)	(2.722)	(2.865)
Av. Homicides, 2000-2004	0.001***	0.002***	0.003***	0.014***	0.016***	0.030***
	(4.120)	(2.201)	(3.319)	(8.478)	(4.612)	(9.268)
Arrests Narcotics Per Capita	-0.109***	0.442***	0.333***	-0.094***	0.435***	0.340***
	(-2.623)	(6.555)	(5.191)	(-2.498)	(7.697)	(6.976)
Port	0.1581	1.062**	1.220**	0.097	0.447	0.545
	(1.163)	(2.500)	(2.470)	(0.745)	(1.242)	(1.284)
Distance to U.S. Border	0.020	-0.152*	-0.132*	0.244***	-0.514**	-0.269**
	(0.349)	(-1.648)	(-1.874)	(2.874)	(-3.969)	(-3.009)

* p<0.10, **p<0.05, ***p<0.01

Appendix

Table A1. Summary Statistics of the Variables included in the Analysis

Variable	Year	Source	Mean	SD
Total Homicide Rates	2005-2010	Estadisticas Vitales, Datos de Mortalidad, INEGI.	12.5	18.6
Youth Unemployment	2000	Censo General de Poblacion y Vivienda 2000, INEGI.	0.2	0.7
Schooling Years	2000	Censo General de Poblacion y Vivienda 2000, INEGI.	1.6	0.3
Gini Index	2005	Consejo Nacional de Evaluacion de la Politica Nacional, CONEVAL.	-0.9	0.1
% Births without SS	2005	Secretaría de Salud/Dirección General de Información en Salud, Estimaciones con base en las Proyecciones de la Población de México 2005 - 2030.	4.2	0.4
% Agricultural Employment	2000	Censo General de Poblacion y Vivienda 2000, INEGI.	3.5	1.0
% Interstate Migrants	2005	Conteo de Poblacion y Vivienda 2005, INEGI.	2.2	1.2
% Administration Justice, 2005	2005	Registros administrativos, Estadisticas judiciales en materia penal, INEGI.	3.0	0.5
% Divorced	2005	Registros administrativos, Estadisticas vitales, INEGI.	12.8	6.6
Arrests Narcotics per capita	2005	Registros administrativos, Estadisticas judiciales en materia penal, INEGI.	66.8	449.0
Port (entry/exit) drug trafficking	2010	Rhoda and Burton (2010)		
Distance to the U.S. border		Own elaboration.	739.9	269.4
Distance to the nearest capital		Own elaboration.	105.4	75.7