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Spillover Effects on Homicides across Mexican Municipalities: A Spatial Regime Model Approach*

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Abstract: This paper investigates the existence of spatial regimes of high violence levels across Mexican municipalities. Our approach consists of providing a framework to explicitly address spatial heterogeneity, which might suggest instability in the structural determinants of homicides. In this context, a distinction is made in relation to the regimes in municipalities within states with long-standing trafficking activities by comparing those municipalities that have been exposed to joint operations (*operativos conjuntos*) and those that were not exposed to the operations. Spatial econometric models were estimated for each regime to investigate 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 not in the 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 estimates of indirect effects, 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

JEL Codes: C21, K42, Y80

1. INTRODUCTION

In the mid-2000s, particular regions of Mexico experienced a remarkable increase in violence levels. Between 2006 and 2010, the most violent scenarios arose in areas with a intensive and long-standing presence of drug-trafficking organizations (DTOs or cartels). It has been argued that the disputes between the DTOs concerning control over specific territories has been a major contributing factor to the increase in violence when compared with prior periods of relatively stable crime trends.

The causes, consequences, or factors associated with contemporary violence and organized crime in Mexico have recently attracted the attention of scholars from different disciplines. In this sense, the context in which the rising violence in Mexico has taken place can

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be framed in reference to past violence trends, regional location of DTOs' activities, supply and demand shocks of illicit drugs, and domestic policies that the federal government has implemented to bolster law enforcement in specific regions of the country. Specifically, some studies have been devoted to the influence of international drug markets (Castillo et al., 2013), the presence of drug-trafficking organizations (DTOs) (Dell et al., 2014; Reuter et al., 2009), state-sponsored protection rackets within the country (Snyder and Duran, 2009), the impact of internal and external shocks such as international agricultural shocks (Dube et al., 2014), the expiration of the U.S. Federal Assault Weapons Ban (Dube et al., 2013), and the effect of the deployment of armed forces in what was known as *operativos conjuntos*, which aimed to recover control of particular areas in the country (Osorio, 2013, 2015; Rodriguez-Oreggia and Flores, 2012).

In most of these studies, the role of geography, whether explicitly considered or not, is a crucial aspect. This is because of the well-defined patterns of the distribution of past and contemporary violence levels across the country as well as the presence of DTOs. On the one hand, drug-trafficking activities from Mexico to the U.S. have very long-standing roots. They date back to at least the mid-1980s when Colombian cartels extended their influence to the United States via drug-trafficking networks, particularly after the successful enforcement efforts by Colombian authorities against the Colombian Cali and Medellin cartels that eventually gave rise to the emergence of Mexican DTOs. Previously, Colombians had trafficked cocaine through Florida (Payan, 2006). Mexican smugglers formed ties with Colombian traffickers and relocated the activity to Mexico's northern border. On the other hand, DTOs have taken advantage of the rugged terrain of the mountains to plant marijuana and opium and, more recently, to produce synthetic drugs. The region referred to as the Golden Triangle—formed by the states of Chihuahua, Durango, and Sinaloa—has historically been a major producer of illicit drugs (Vinson, 2009). There is evidence to suggest that the mountainous terrain has a positive relationship with the proliferation of armed conflict, which eventually translates into rising homicide rates (Fearon and Laitin, 2003).

Though drug trafficking and related violence have become serious problems and have hindered the government and national security, the concerns do not apply to the whole territory but only to particular areas. In such areas, the levels of violence as measured by homicides have soared dramatically since the end of 2006. The unprecedented and increasing levels of violence have been attributed to confrontation among DTOs, especially after the deployment of federal armed forces to combat these organizations and to eliminate criminal control over public spaces.

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

Although illegality does not necessarily breed violence, the relationship between these illicit markets and violence depends on institutions of protection. When state-sponsored protection rackets form, illicit markets can be peaceful. Conversely, the breakdown of state-sponsored protection rackets, which may result from different factors, can lead to violence. As argued by Snyder and Duran (2009), the cases of drug trafficking in contemporary Mexico and

Colombia show how a focus on the emergence and breakdown of state-sponsored protection rackets helps to explain variation in levels of violence, both within and across illicit markets.

The territorial distribution of crime in Mexico, therefore, suggests a diverse profile of crime, making heterogeneity the rule; no general pattern for the whole country can explain such a rise in violence (Escalante, 2010). This raises some methodological issues, as our unit of analysis consists of geographic units. First, the spatial structure of the data represents connectivity; e.g., crime in one territorial unit may influence crime in other units. This sort of spatial dependence should be explicitly taken into account in the empirical analysis. Second, the distribution of homicides may be uneven across space, pointing to some sort of spatial heterogeneity in that distribution. This in turn may lead to the identification of spatial regimes of violence associated with a particular state or other administrative borders, with potential cross-administrative dimensions or some spillover effects, of this violence as well (Ingram, 2014).

Our approach in this paper 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 arising from the fact that rising violence levels appeared within specific regions of the country. These specific areas have exhibited higher homicide rates for a long period of time than other areas within the country. In modeling this process, we investigate spatial diffusion patterns of high levels of violence to nearby locations while explicitly controlling for the possible effect of increasing law enforcement resources resulting from the joint operations. 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 2 outlines the context of increasing violence in Mexican regions and discusses preliminary evidence to suggest the use of spatial regimes; Section 3 introduces the spatial methods to be used in the analysis, along with the description of the database. The fourth section presents the corresponding test supporting the convenience of applying spatial regimes models and provides evidence of some spillover effects arising from some variables included in the analysis. Finally, we draw some conclusions.

1.1 Context and Motivation for Spatial Regimes

In this section we briefly discuss the motivation for framing our analysis by what is known in the literature as spatial regimes models. The interest for us lies in providing some insights into how and why we should expect spatial regimes to exist, and in what ways the determinants of homicide might differ across geographic areas. Does the spread of homicides work differently in some regions of the country?

The fact that current and past violence levels, in this case the distribution of homicides across municipalities, have persistently been higher in some regions of the country, indicates distinctive geographic patterns that may cast evidence about some sort of spatial heterogeneity. This in turn could lead to the formation of some geographic subgroups. Spatial heterogeneity refers to the uneven distribution of a trait, event, or relationship across a region (Anselin, 2010).

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 was a fight between different drug cartels to control geographical areas that led to joint military operations (*Operativos Conjuntos Militares*) run by the federal and state governments. 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 those near the border with the U.S. (Sanchez, 2011). In fact, when analyzing the spatial distribution of past homicides, 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.

The two scenarios have one characteristic in common: 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. In these states there has also been a bloody struggle among drug organizations to control the territory (see Figure 1).

Figure 2 displays four maps describing the spatial distribution of homicides in Mexico in 1990, 2000, 2005, and 2010; the last two dates correspond to the period analyzed here. 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. The past and current patterns motivate our exploration of different regimes, as the results will likely play a role in explaining the rise in and the location of the violence.

Figure 1: Mexican States with Army Intervention as Part of the "Joint Operations"

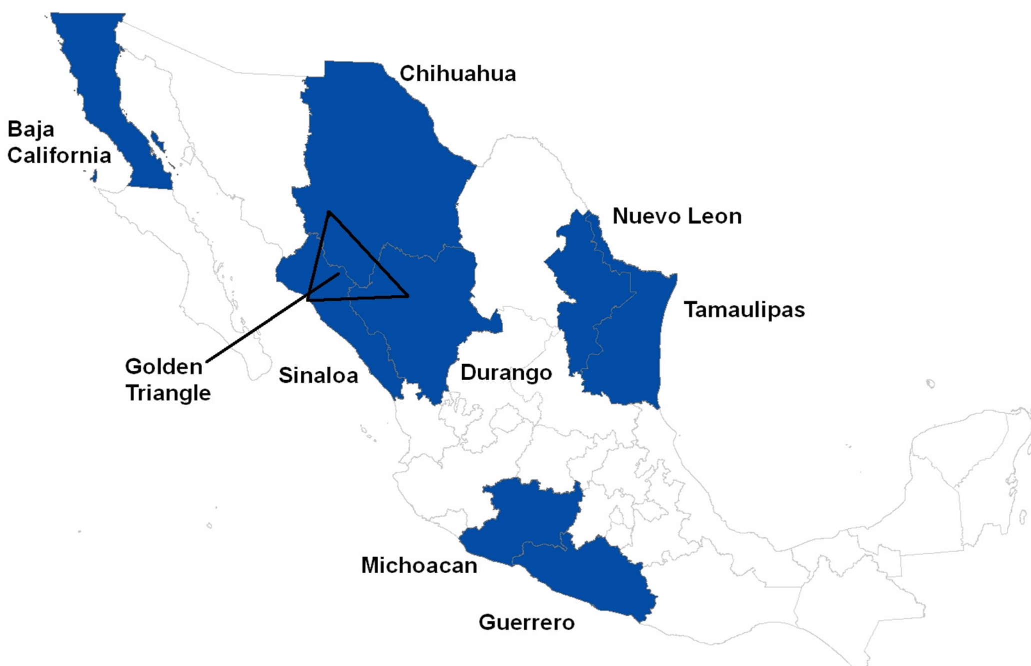


Figure 2: Spatial Distribution of Homicide Rates in Mexico—1990, 1995, 2000, and 2005

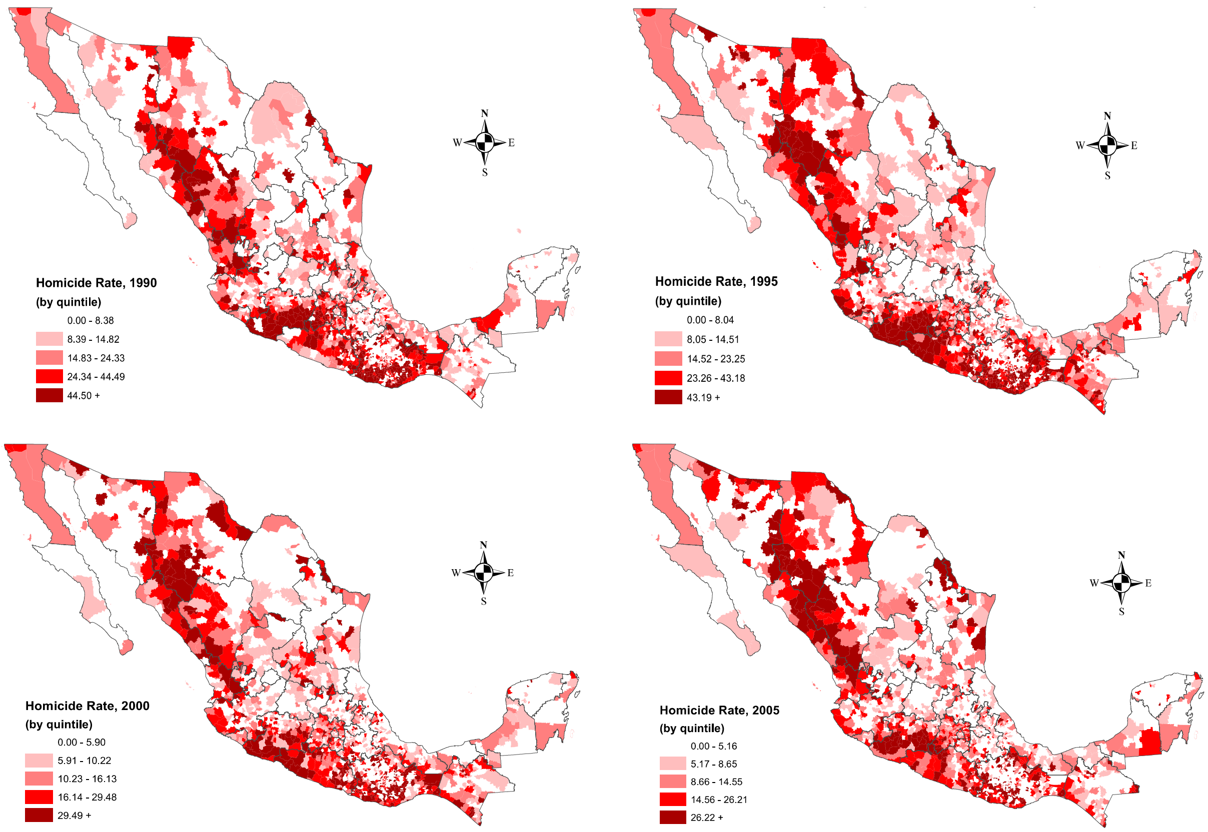
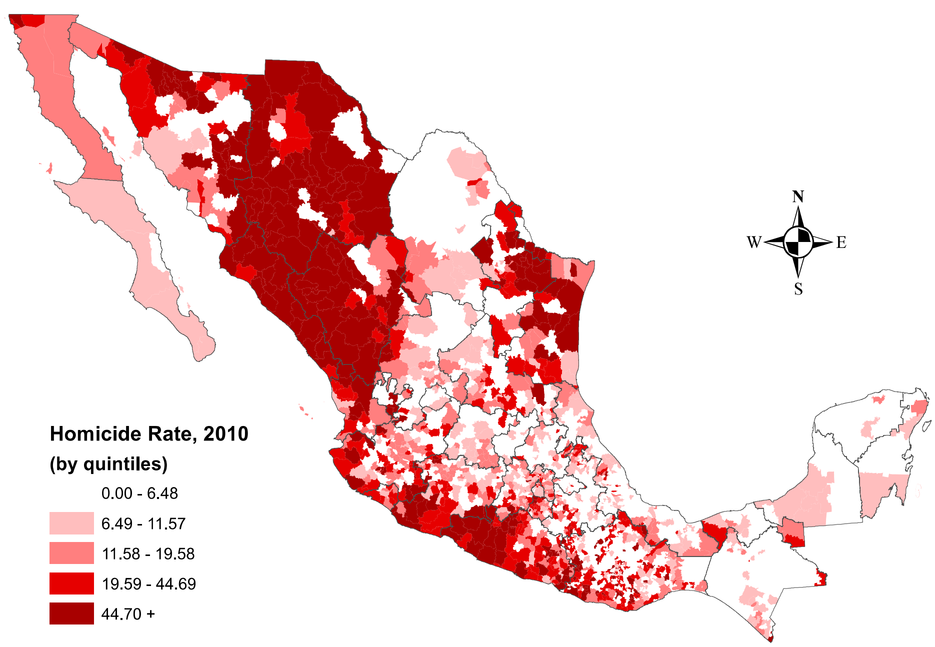


Figure 3: Spatial Distribution of Homicide Rates in Mexico in 2010



But how might regions with long-standing drug-trafficking activities or the presence of DTOs be associated with an increase in violence? The answer could be grounded in what is known as the theory of contingent causation. This states that the likelihood of increased violence is directly related to drug market activities, which are contingent on, among other factors, the social circumstances present in the marketplace. Specifically, Zimring, and Hawkins (1999, p. 153) argue that "the creation and expansion of illegal markets will produce extra homicides when social circumstances conducive to lethal violence exist."

Mexico is an interesting case to study due to the interaction of anthropological factors that have led to the rise of a "narco culture" in some areas of the country. The orchestrated acts of violence, videos, graffiti, signs and banners, blogs, and narco-ballads exalting major drug traffickers and their exploits have risen as manifestations of Mexican drug cartels (Campbell, 2012; Williams, 2009). Rather than just being a form of criminal behavior that is purely associated with violence, drug trafficking is the quasi-ideological expression of criminal organizations that, along with their allies among the police, the military, and the politicians, control vast territories and have taken on many functions of the state (Campbell, 2012; Snyder and Duran, 2009).

Presumably, these cultural orientations might be conducive to comparatively high levels of homicides in specific regions (Messner et al., 2005). For the purposes of the present research, it is plausible to hypothesize that some contextual factors might be associated with homicides in those states with long-standing presence of DTOs and drug-trafficking activities. As discussed above, the implementation of joint operations took place precisely in those regions. Hence, it is convenient to test spatial regimes models given the cross-sectional setting of our data as well as the lack of credible instruments for effectively assessing the effect of the joint operations. Instead, we opt to test the existence of spatial regimes and consequently estimate the effect of important covariates associated with homicides. The use of spatial econometric modeling allows us to estimate the respective direct and indirect effects of these covariates for each regime.

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 is described. Finally, a formal specification of the econometric model addressing the direct and indirect effects (the latter associated with spillover effects) is presented.

2. METHODS AND DATA

2.1 ESDA for Detecting Spatial Regimes in the Distribution of Homicides

Spatial regimes are a form of spatial heterogeneity when 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 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. Specifically, a local version of the Moran's I – also known as LISA – is used to analyze the nature of the local distribution of homicides. 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. The first two arise 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.

2.2 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, where each regime is characterized by differing parameter values or functional forms (e.g., crime in certain regions might be structurally different from crime in other regions). 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). 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:

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

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:

$$C = \left[\frac{(e_R' e_R - e_U' e_U)}{K}\right] \left[\frac{(e_U' e_u)}{(N - 2K)}\right] \sim F_{(K,N-2K)} \tag{2}$$

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 (Anselin, 1990, 1998):

(3) $$C = [e_R'(\mathbf{I} - \lambda\mathbf{W})'(\mathbf{I} - \lambda\mathbf{W})e_R - e_U'(\mathbf{I} - \lambda\mathbf{W})'(\mathbf{I} - \lambda\mathbf{W})e_U]/\sigma^2 \sim {\chi^2}_K$$

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 n x n.

2.3 Data-Generating Process

In modeling homicide rates, the rate in any particular municipality 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 settings, the reader is referred to LeSage and Pace (2009) or the work of Elhorst (2014) in relation to panel data.

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

(4) $$\boldsymbol{y} = \rho\mathbf{W}\boldsymbol{y} + \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$$

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

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

where **y** denotes an n x n array 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 $w_{ij} = 0$ 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 $\sigma^2\mathbf{I_n}$, where $\mathbf{I_n}$ denotes an n x n identity matrix.

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

(7) $$\mathbf{y} = \rho\mathbf{W}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \mathbf{W}\mathbf{X}\theta + \boldsymbol{\varepsilon}$$

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

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

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:

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

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:

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

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

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

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

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

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

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

$$y = (\mathbf{I_n} - \rho\mathbf{W})^{-1}(\mathbf{x_1}\boldsymbol{\beta_1} + \mathbf{x_1}\mathbf{x_2}\boldsymbol{\beta_2}) + (\mathbf{I_n} - \rho\mathbf{W})^{-1}\mathbf{W}\mathrm{x}_1(\boldsymbol{\theta_1} + \mathbf{x_2}\boldsymbol{\theta_2}) + (\mathbf{I_n} - \rho\mathbf{W})^{-1}\varepsilon. \tag{15}$$

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

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

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

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

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

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 from which the change originated (observation *i*) (LeSage and Pace, 2009).

Formally, for each model specification an n x n matrix arises from the partial derivatives described above, where the direct effects are calculated from the average of the main diagonal elements (own-partial derivatives), while the cumulative sums of off-diagonal elements for each row reflect 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. The t-statistics show which variables produce (statistically significant) spatial spillover impacts. For such purposes, the appropriate routines in R software are used.

2.4 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) 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 República. 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 occurred with extreme violence or as an event involving more than two victims, and they include at least two of the following criteria: An injury resulting from the use of a firearm; torture and severe injuries; a body found in the interior of a vehicle; materials characteristic of the modus operandi of organized crime; and any particular facts related to the death, such as the event occurring in the context of an ambush or a persecution or the existence of a message linked to organized crime.

Note, 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 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.

All data come from officially collected databases, and the summary of the variables is presented in Table A1 in 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 illustrate the trend in crime at the local level.

The rate of youth unemployment is one variable that may be a determinant of 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 consequences associated with crime, reducing the incidence of crime.

Inequality may have an incidence on social dissolution and may lower the rewards for lower income individuals of being involved in legal activities. Here, we have used the Gini Index at the municipal level as calculated by the Consejo Nacional de Evaluación de la Política 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 the formal sector of the economy has social security benefits by law, allowing his 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 (Guerette, 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 the municipal level were not available when this study was conducted. 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 law enforcement efforts in a given municipality.

Population density, here measured as the total population in each municipality per unit square (km^2), is often included as a control variable and is highly associated with the volume and type of crime occurring. Another variable, the distance from each municipality to the closest state capital, whether or not the municipality belongs to the state, is also included, aimed at capturing access to potential markets that in turn is related to greater returns on trafficking activities. 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 municipalities 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 variable if a particular municipality has been identified as a port for entry of drugs into the country, as reported by Rhoda and Burton (2010).

3. RESULTS

3.1 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 above average homicide rates that are surrounded by neighbors whose homicide rates are also above average. Note that the HH cluster type reached its highest level 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.

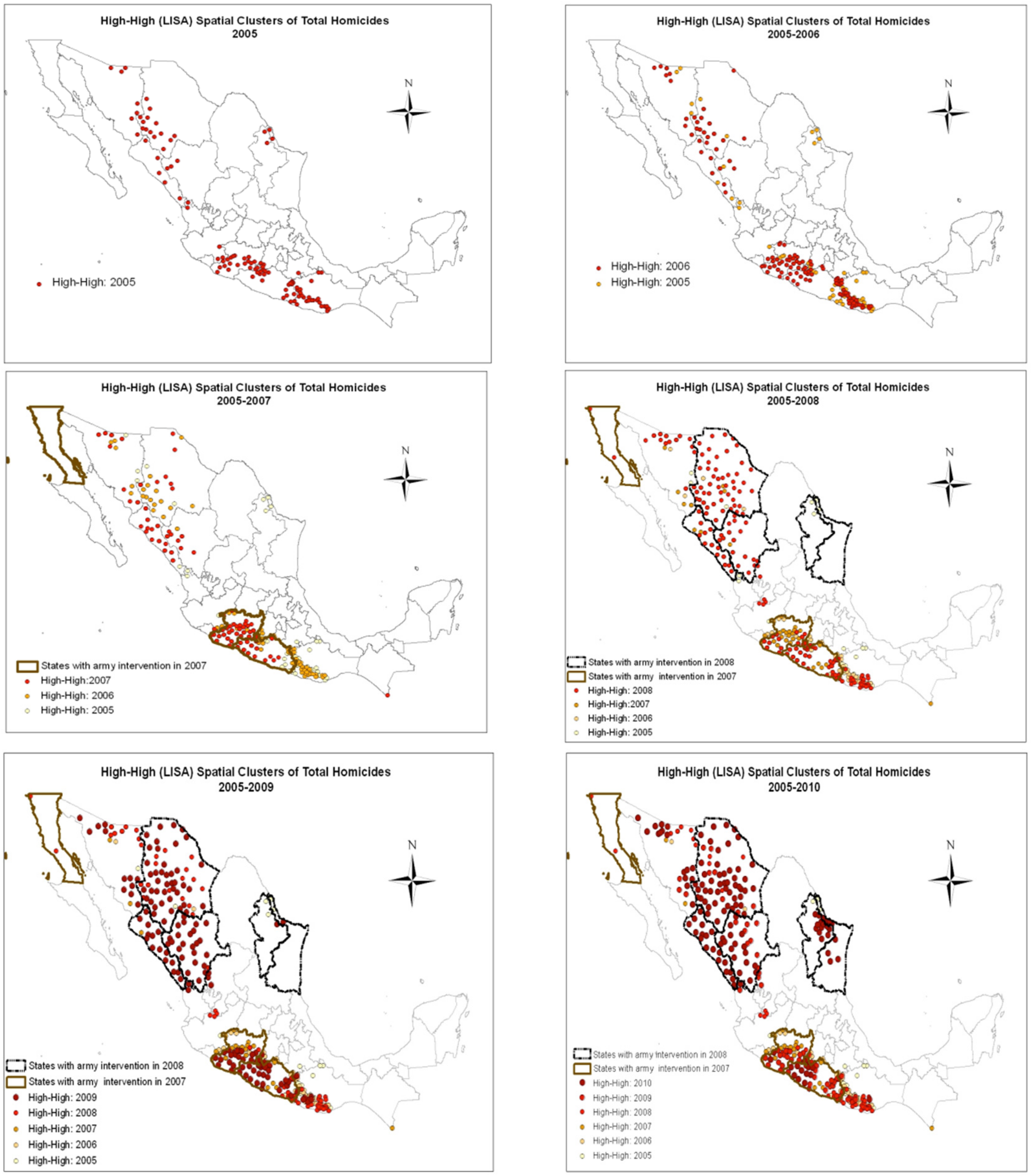
The geographic diffusion patterns followed by the HH clusters are also noteworthy. In Figure 4 it is possible to distinguish the states that are subject to joint operations as well as the distribution of the HH cluster from 2005 to 2010. The latter are displayed as centroid circles with a graduated color 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.

Table 1: Percentage of Municipalities with Statistically Significant LISA Values

	Year					
LISA Cluster	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

Number of municipalities expressed in parentheses.

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



3.2 Spatial Regimes Results

In examining the possibility of spatial regimes in homicide rates, the selection of the regimes is supported on visual inspection and the ESDA analysis described above. 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 show 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 the different model specifications discussed previously, although we only report the spatial Chow test that 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.

Once the existence of spatial regimes in the spatial variation of homicides has been defined and formally tested, the next step consists of estimating spatial econometric models in light of 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 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 are somewhat similar in the spatial lag and spatial Durbin models, even after controlling for other explanatory covariates.

Table 2: Spatial Chow Test OF

	No Joint Operation		Joint Operation		Structural differences in correlates
Variable	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient
Gini Index, 2000	0.288***	(0.0766)	-0.377	(0.4203)	2.423
Schooling Years, 2000	-0.006	(0.0283)	-0.031	(0.1375)	0.034
% Agricultural Employment, 2000	-0.002	(0.0133)	0.050	(0.0505)	1.048
Administration of Justice, 2005	-0.074***	(0.0223)	-0.034	(0.1256)	0.101
Youth Unemployment, 2000	-0.007***	(0.0131)	-0.060	(0.0538)	0.91
% Births without SS, 2005	0.096***	(0.0263)	-0.024	(0.1307)	0.815
% Interstate Migrants, 2005	-0.021	(0.0083)	0.004	(0.0399)	0.282
% Divorced	0.039***	(0.0147)	0.045	(0.0701)	0.007
Population Density	0.004	(0.0050)	-0.024	(0.0247)	0.621
Av. Homicides, 2000-2004	0.001	(0.0003)	0.010***	(0.0024)	12.27***
Port	0.481***	(0.1638)	-0.215	(0.2444)	5.614***
Arrests Narcotics Per Capita	0.250***	(0.0489)	0.220**	(0.1176)	0.059
Distance to U.S. Border	-0.097***	(0.0318)	0.052	(0.0836)	2.811*
Distance nearest Capital	0.048*	(0.0250)	-0.122	(0.0977)	2.874*
Intercept	-0.083	(0.1747)	-0.399	(0.8821)	0.124
Spatial Lag Parameter (ρ)	0.377***	(0.1038)	0.748***	(0.1048)	6.32
Global test					53.372***

Standard errors are in parentheses. *p<0.10, **p<0.05, ***p<0.01

3.3 Estimated Direct and Indirect Effects Results

The final set of results, which describes direct and indirect effects, is estimated with 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) indicate and that might be present in our estimates: (1) there is one (or 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 ρ and W but also on the coefficient estimate θ_k. In other words, the SDM does 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).

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 statistical 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. Administration of justice shows a significant and negative expected effect (-0.010) on homicide rates in the nonjoint operation regime, although the magnitude of the effect and statistical significance appears to be limited. For the same type of spatial regime, family disruption tends to have a positive direct effect on homicide rates (0.038), as do informality levels, which tend to positively influence homicide rates (0.101). 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 0.013, 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 (-0.113 and -0.099, respectively).

Interesting results arise from the estimation of indirect effects that, as discussed above, are associated with spillover effects. While proximity to the nearest capital shows significant indirect and total effects on homicides in both regimes, population density lacks statistical significance. Hence, access to potential markets seems to be capturing much of the positive effect on homicides. Furthermore, historical levels of homicides, and distance to the U.S. border exhibit significant indirect effects in both regimes, but the estimates are approximately three times higher in magnitude in the joint operations regime. Conversely, the indirect effects of income inequality, administration of justice, agricultural employment, and port of entry or exit for drug trafficking are statistically significant only in the non-joint operation regime, while exhibiting the expected effect.

These results suggest some 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 homicide rates while generating a negative spillover effect, the magnitude of which seems to overcome the estimated direct effect. Furthermore, being proximate to a port of entry or exit for drug

Table 3: SDM Estimated Coefficients

	No Joint Operation		Joint Operation	
	Coefficient	Std. Error	Coefficient	Std. Error
Gini Index, 2000	0.287***	(0.1061)	-0.725*	(0.3058)
Schooling Years, 2000	-0.026	(0.0360)	-0.018	(0.0884)
% Agricultural Employment, 2000	0.02	(0.0245)	0.015	(0.0460)
Administration of Justice, 2005	0.001	(0.0498)	-0.138	(0.1334)
Youth Unemployment, 2000	-0.009	(0.0167)	-0.032	(0.0365)
% Births without SS, 2005	0.101***	(0.0338)	-0.193**	(0.0942)
% Interstate Migrants, 2005	-0.014	(0.0121)	0.021	(0.0301)
% Divorced	0.037*	(0.0191)	0.041	(0.0482)
Av. Homicides, 2000-2004	0.001***	(0.0004)	0.013***	(0.0017)
Arrests Narcotics Per Capita	-0.137***	(0.0426)	-0.120***	(0.0392)
Port	0.093	(0.1242)	0.123	(0.1246)
Distance to U.S. Border	0.036	(0.0608)	0.312***	(0.0881)
Distance nearest Capital	-0.006	(0.0410)	-0.027	(0.0384)
Pop. Density	0.011***	(0.0016)	-0.113***	(0.0296)
Intercept	0.183	(0.1269)	-0.530***	(0.0628)
W Av. Homicides, 2000-2004	0.004	(0.0005)	0.006***	(0.0029)
W Gini Index, 2000	0.094	(0.1591)	0.758	(0.5244)
W Schooling Years, 2000	0.022	(0.0621)	-0.014	(0.1819)
W % Agricultural Employment, 2000	-0.069**	(0.0350)	-0.121*	(0.0894)
W Administration of Justice, 2005	-0.124**	(0.0573)	0.209	(0.1735)
W Youth Unemployment, 2000	-0.025	(0.0317)	-0.273***	(0.0813)
W % Births without SS, 2005	-0.051	(0.0563)	0.468***	(0.1398)
W % Interstate Migrants, 2005	-0.006	(0.0178)	-0.158***	(0.0536)
W % Divorced	0.001	(0.0333)	0.1856*	(0.0920)
W Port	0.563**	(0.2348)	0.276	(0.2434)
W Arrests Narcotics Per Capita	0.302***	(0.0546)	0.337***	(0.0475)
W Distance to U.S. Border	-0.112	(0.0753)	-0.473***	(0.1238)
W Distance nearest Capital	0.150***	(0.0508)	0.104**	(0.0456)
W Population Density	0.021	(0.0203)	0.096**	(0.0474)
ρ	0.355	(0.0238)	0.455	(0.0263)
N	2,039		417	
Wald	363.25		182.04	
LR test	314.2		166.92	
AIC	3,360.4		3,158.4	
Log likelihood	-1,649.21		-1,548.183	

W denotes the spatial lag of the respective variable. Standard errors are in parentheses. *p<0.10, **p<0.05, ***p<0.01

Table 4: SDM Estimation of Direct, Indirect, and Total Effects

Variable	No Joint Operation			Joint Operation		
	Direct	Indirect	Total	Direct	Indirect	Total
Gini Index, 2000	0.309***	0.392**	0.702***	-0.690***	0.741	0.051
	(3.0022)	(1.6932)	(3.0090)	(-2.3219)	(1.0793)	(0.0962)
Schooling Years, 2000	-0.025	0.017	-0.007	-0.020	-0.032	-0.052
	(-0.7336)	(0.1702)	(-0.0727)	(-0.2067)	(-0.0992)	(-0.1539)
% Agricultural Emp., 2000	0.014	-0.103**	-0.089*	0.007	-0.172	-0.164
	(0.6190)	(-2.0710)	(-1.8375)	(0.1404)	(-1.4478)	(-1.4011)
Administration of Justice, 2005	-0.010*	-0.216*	-0.227*	-0.127	0.237	0.110
	(-0.2316)	(-3.1905)	(-4.6690)	(-1.0146)	(1.1675)	(0.6559)
Youth Unemployment, 2000	-0.012	-0.051	-0.063	-0.052	-0.422	-0.474
	(-0.7129)	(-0.9817)	(-1.1171)	(-1.3743)	(-1.5740)	(-1.6720)
% Births without SS, 2005	0.101***	-0.009	0.091	-0.165*	0.591***	0.426***
	(3.1583)	(-0.1045)	(1.0270)	(-1.8063)	(3.3706)	(2.7870)
% Interstate Migrants, 2005	-0.016	-0.022	-0.038	0.010	-0.223***	-0.212***
	(-1.4316)	(-0.8335)	(-1.4524)	(0.3378)	(-3.0346)	(-2.8006)
% Divorced	0.038**	0.029	0.068	0.055	0.296**	0.352**
	(2.0258)	(0.5666)	(1.1981)	(1.1686)	(2.2788)	(2.5012)
Distance nearest Capital	0.008	0.256***	0.265***	-0.020	0.139***	0.119***
	(0.2467)	(3.7438)	(4.2653)	(-0.5856)	(2.6088)	(2.9059)
Population Density	0.009	-0.029	-0.020	-0.109*	0.083	-0.025
	(0.6046)	(-1.0910)	(-0.8901)	(-1.8487)	(1.3646)	(-0.4452)
Av. Homicides, 2000-2004	0.001***	0.002***	0.003***	0.013***	0.016***	0.030***
	(4.2421)	(2.2827)	(3.3512)	(8.5087)	(4.5105)	(8.9354)
Arrests Narcotics Per Capita	-0.113***	0.416***	0.302***	-0.099***	0.436***	0.337***
	(-2.7613)	(5.5127)	(4.0323)	(-2.6636)	(7.8279)	(7.11083)
Port	0.152	1.054**	1.207**	0.145	0.473	0.619
	(1.1545)	(2.4891)	(2.4660)	(1.11808)	(1.2654)	(1.4228)
Distance to U.S. Border	0.0267	-0.166*	-0.140*	0.286***	-0.536***	-0.250**
	(0.4821)	(-1.8161)	(-1.9082)	(3.4759)	(-3.5875)	(-2.1458)

Simulated *z*-values are in parentheses. **p*<0.10, ***p*<0.05, ****p*<0.01

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 (0.591), 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 are 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 both of the regimes (0.333 and 0.349, respectively). 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.

4. FINAL DISCUSSION

In this paper, we have aimed to analyze the extent of the diffusion of crime, measured with homicides, between 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 to have increased in other nearby localities. 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.

A LISA analysis suggests an increase in clusters of homicides for the period of consideration. 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 states 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 with regards 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 nonjoint operation regime, a historical level of homicides and closeness to the U.S. border are more important 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 noteworthy. 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. Nonetheless, the fact that some covariates such as informality, divorce rates, and administration of justice showed distinct effects across regimes draws attention to the permeability of the "narco" phenomenon in relation to contextual and institutional factors. Further investigation on this subject is suggested.

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' rights 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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