The Local Educational and Regional Economic Foundations of Violence: A Subnational, Spatial Analysis of Homicide Rates across Mexico's Municipalities

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Abstract. Violence diminishes wellbeing, and public insecurity erodes the rule of law, undermining the quality of democracy and constraining business and commercial interactions. A better understanding of the origins of violence is therefore crucial. Examining 2010 homicide rates across Mexico's 2455 municipalities, this paper offers a subnational and spatial study of the patterns and sources of violence. Offering the first spatial Durbin model of homicide in Mexico, the analysis generates novel and rich findings. Core findings include (1) homicide is not randomly distributed across municipalities, (2) homicide rates follow a spatial lag effect, suggesting violence in one community spills over into neighboring communities, (3) education has a meaningful protective effect against violence, but this is only a local, direct effect; and (4) economic *in*activity exerts an unexpectedly negative direct effect, but a strong positive indirect effect from neighboring communities; that is, when economic conditions deteriorate in nearby communities, local violence increases, suggesting homicide is committed locally but by individuals in economically depressed, outlying areas. Violence-reduction policies, then, require coordination across nearby communities and should proceed on two fronts: (a) localized improvements in education attainment, which can be addressed within individual jurisdictions, and (b) economic development policies targeted at intermediate regions below the state level but above the municipal level, which require cross-jurisdictional collaboration, even by municipalities across state boundaries – what I refer to as a "local-schools/regional-economy" approach to violence prevention.

INTRODUCTION

Violence diminishes individual and community wellbeing, and public insecurity erodes the rule of law, undermining the quality of democracy and constraining business and commercial transactions. In Latin America, persistently high levels of violent crime threaten the stability of new and consolidating democracies, calling out for better explanations of this violence that can inform public policy. These explanations are particularly important given that frustration with persistently high crime rates after transitions to democracy has generated broad support for heavy-handed authoritarian policies and decreased support for democracy (Seligson 2004, cited in Mainwaring, Scully, and Cullell 2010, 31). In some post-transition settings, e.g., El Salvador, clear majorities support a return to authoritarian government (Sarles 2001, 49, citing Seligson, Cruz, and Cordova 2000). Insecurity also generates costs for business and dissuades investment, so violence hinders economic growth (Prillaman 2003). Gaining a better understanding of the origins of violence in order to design better violence-reduction policies, therefore, is critical.

In Mexico, violent crime garners daily media attention, and the years since 2006 have seen a dramatic increase in homicides (Molzahn, Rios, and Shirk 2012). In part as an attempt to respond to high crime and impunity, a revolutionary criminal justice reform began in 2008, funded and sponsored in part by the U.S. Agency for International Development. However, this reform has been criticized for including policies that are heavy-handed and impinge on due process rights, and for being too focused on formal institutions and neglecting broader social policies (e.g., Ingram and Shirk 2012). That is, the reform, like others in the region, emphasizes a more efficient justice-sector response to crime while neglecting a large literature addressing the root social and economic causes of crime, i.e., why crime occurs in the first place. In this context, studies that can shed light on the sources of violent crime in Mexico are politically salient, relevant to ongoing policy formation, and address a major domestic security crisis in a close U.S.

neighbor and trading partner. Further, given the concerns that patterns of violence in Mexico may influence violence in the U.S., understanding the sources of violence in our southern neighbor is a pressing domestic issue.

Examining 2010 homicide rates across Mexico's 2455 municipalities, this paper offers a subnational and spatial study of the patterns and causes of violent crime. Systematic data on crime, especially different types of violent crime over time, are unavailable across Latin America and other parts of the developing world. However, homicide is one crime for which data are generally available, it has the greatest impact on wellbeing and the quality of life in democratic societies, and other types of crimes tend to be correlated with the incidence of homicide (Mainwaring, Scully, and Cullell 2010, 31; Bailey and Dammert 2006, 7). Subnational analyses of homicide can leverage within-country variation to provide a more fine-grained picture of the origins of violence that whole-nation comparative studies overlook. Further, a municipal perspective allows the identification of spatial regimes of violence that may straddle state or other administrative borders, pointing to the cross-jurisdictional dimensions of this violence. Adding the spatial perspective addresses the dependent structure of the data, explicitly accounting for the fact that geographic units are linked together, and crime in one territorial unit may influence crime in other units.

Spatial analysis has been slow to spread in political science, especially comparative politics. Indeed, to the author's knowledge, this is the first study to apply a spatial Durbin model to the study of homicide in Mexico, and is only the second application of this model to the study of homicide (see Ruther 2013). Novelty aside, a key analytic strength of spatial Durbin models is the ability to generating rich interpretations from the results, much richer even than conventional spatial econometrics, including the estimation of both within-unit (direct) and neighborhood (indirect) effects, as well as the persistence or decay of these effects across higher order of neighbors. In short, a Durbin model generates a much finer picture of spatial processes underlying the data, addressing the nature of these processes for both the outcome of interest and the explanatory variables. For these reasons, Durbin models are regarded as the state of the art in spatial analysis (Ellhorst 2010; Yang et al. 2013).

Looking ahead, core findings include (1) the identification of spatial clusters or "hot zones" of homicide within Mexico, several of which straddle multiple state boundaries, raising questions about the special, cross-jurisdictional challenges of designing violence-reduction policies; (2) a spatial lag effect of violence, suggesting violence in one community spills over into neighboring communities; (3) education has a meaningful protective effect against violence, but this is only a local, direct (within-unit) effect; and (4) economic inactivity exerts an unexpectedly negative direct effect, but a strong positive indirect effect from neighboring communities; that is, when economic conditions deteriorate in nearby communities, local violence increases, suggesting homicide is committed locally but by individuals in economically depressed, outlying areas. Violence-reduction policies, then, should proceed on two fronts: (a) localized improvements in education attainment, which can be addressed within individual jurisdictions, and (b) economic development policies targeted at intermediate regions – below the state level but above the municipal level, even straddling state boundaries – which require cross-jurisdictional collaboration, what I refer to as a "local-schools/regional-economy" approach to violence prevention.

HOMICIDE RATES IN MEXICO'S MUNICIPALITIES

Figure 1 reports a decile map of 2010 homicide rates across Mexico's 2455 municipalities. In the decile map, light colors identify municipalities with low homicide rates, and the color darkens as the homicide rate increases. The darkest brown areas identify the municipalities with the highest homicide rates. Even a cursory glance at this kind of map reveals that there are concentrations of darker, violent areas in (1) the upper, west coast of Mexico (across the states of Nayarit, Sinaloa, and Sonora), (2) the northeast (covering parts of three states: Coahuila, Nuevo Leon, Tamaulipas), (3) southern Mexico, and (4) portions of the Yucatan peninsula in the southeast. In contrast, there are a few areas in northern, central, and southern Mexico that are almost clear of any color, i.e., have low homicide rates.

[Figure 1 about here]

Conventionally, homicide rates count the number of homicides per 100,000 people. Based on official government statistics (see Data section), Mexico's national homicide rate in 2010 was 14. This number was almost three times that of the U.S. that year, which was 4.8 (FBI 2011). However, these national figures conceal substantial variation in both countries. In the U.S., the highest rates are reported by cities like Detroit, New Orleans, and Baltimore, but rarely exceed 40. In Mexico, more than 100 municipalities had homicide rates in 2010 that exceeded 100. To be sure, together these communities had a total population below 50,000, and most had populations below 10,000. Still, a very large number of communities lost 1-2% of their population to murder in 2010.

It should also be noted that, in 2010, Mexico was three years into a militarized confrontation with drug trafficking organizations, and the incidence of homicide had been increasing since the early 2000s, and then more dramatically after 2006 (Molzahn, Rios and Shirk 2012). Thus, the national statistics on homicide are capturing both ordinary violence and violence associated with organized crime. However, at least in Mexico, studies have shown that official government statistics for homicides closely track the trends of executions associated with the drug trade (Molzahn, Rios and Shirk).

THEORY

Three main theoretical perspectives guide the empirical analysis, drawing from existing research across the disciplines of sociology/criminology, political science, and demography, respectively. The expectations derived from sociological theory fall into three main categories: population pressures, resource deprivation/affluence, and social disorganization. The expectations derived from the political science literature also fall into three main categories: regime dynamics, social capital, and armed conflict. There is some theoretical overlap between the social disorganization and civil society/social capital arguments, which I discuss further below. Finally, the expectations derived from demography, especially demographic studies of mortality, focus on the contrasting processes of spillover effects and social relativity, that is, that the same explanatory factor can generate positive or negative synergies, respectively, across space.

SOCIOLOGICAL EXPLANATIONS OF VIOLENCE

Sociologists and criminologists have found an association between a large array of demographic, economic, and social features of communities and the rate of crime in those communities. These features included measures of social distance, alienation (or anomie), measures of social disorganization and fragmentation, as well as measures of opportunities for crime. However, in large-N regression analyses seeking to explain variation in crime rates, inconsistent results were common (Baller et al. 2001, 562). In a landmark publication, Land et al. (1990) established that much of this inconsistency was due to multicollinearity among the explanatory variables, and generated three principal components from the primary predictors of interest. These three composite measures captured (1) population structure, (2) resource deprivation/affluence, and (3) family disruption (see discussion by Baller et al, 562, 568). Population structure is frequently operationalized as the principal component of total population (logged) and population density (logged). Resource deprivation/affluence has been operationalized as the principal component of income (median family or per capita), inequality (e.g., Gini coefficient), percent of families that are headed by women, percent below poverty, and percent minority (e.g., percent black). Lastly, family disruption has been measured using divorce rates (Land et al. 1990; Baller et al. 2001).

POLITICAL SCIENCE EXPLANATIONS OF VIOLENCE

While political scientists tend to be more concerned with outcomes broadly classified as political violence – insurgency, rebellion, coup, civil war, terrorism – political scientists are also concerned with the effectiveness of public institutions and governance more broadly. Three areas of research yield testable hypotheses in this study: regime competitiveness, social capital, and the greed/opportunity and grievance perspectives on armed conflict.

First, existing research finds that electoral uncertainty can generate powerful incentives to improve public institutions, including legislative institutionalization (Beer 2003; Solt 2004), electoral districting (Reynoso 2005), fiscal policy and performance (Boyce 2005; Flamand 2006), educational spending (Hecock 2006), and judicial budgets in the Mexican states (Beer 2006; Ingram 2014). Margins of victory and the effective number of parties are frequent measures for competitiveness, but turnover – actual alternation of the party in power – offers evidence that not only are political races close, the incumbent – even a long-standing incumbent – actually lost. Indeed, turnover offers evidence of both electoral uncertainty as well as the likelihood that any illegal networks of crime or corruption have at least been disturbed, if not dismantled. For instance, Snyder and Duran-Martinez's (2009) suggest that state protection rackets that may have existed prior to 2000 were dissolved by the weakening of the formerly dominant party, PRI, in the 1990s. In Mexico this would especially be the case where the PRI held the mayor's office and was then displaced by either of the two main opposition parties (PAN or PRD). However, even if one of the opposition parties had already displaced the PRI and turnover were capturing the return of the PRI, the same logic holds. That is, due to both the incentives generated by electoral uncertainty and the disruption of criminal networks, alternation in power should have a curbing effect on homicide rates.

Second, drawing on the social capital literature (in political science, e.g., Putnam 1994, but also sociology and demography, e.g., Yang et al. 2013), participation should exert a downward pressure on criminal activity. All else being equal, I anticipate that patterns of more intense civic engagement generate the social resources to reduce or even prevent criminal violence. Empirically, cities with a greater degree of citizen involvement and engagement will experience less violence than cities with less of this social capital.

Third, the political science literature on armed conflict and political violence can also be leveraged to identify causes of violent crime. The conflict literature generally posits explanations that highlight one of two key factors: greed/opportunity or grievance. The opportunity arguments suggest that crime is motivated by material interests and therefore material cost-benefit calculations (e.g., Collier and Hoeffler 2001). Thus, individuals join rebel groups or terrorist organizations when there is something material to be gained, and these gains are perhaps most attractive to individuals who are poorer or more resource deprived. In this manner, the opportunity approach to armed conflict overlaps and complements the resource deprivation argument in sociology/criminology, though an implication in the conflict literature is that rebels, insurgents, or dissidents tend to be conceptualized as "greedy criminals", a concept that carries its own normative commitments that frequently need to be examined more closely. In contrast to the greed/opportunity argument, grievance theory contends that armed conflict can have non-material origins, that is, that rebellion or insurgency or political violence can be motivated by a wide range of ideational factors – including revenge, duty, a sense of injustice, or ideology – that may not respond predictably to material cost-benefit calculations. Indeed, actors motivated by deeply held grievances may appear to be engaging in highly risky or costly behavior (e.g., McAdam 1986; Ingram 2012). In this regard, the grievance explanation overlaps with the sense of frustration or injustice that can result from resource deprivation and high inequality, though the motivation for action is different. Grievance raises questions of the legitimacy of laws and justice institutions. For instance, Family (2009) finds that Mexican migrants to the U.S. report a greater willingness to enter the U.S. illegally if they perceive the U.S. immigration laws as illegitimate. At the domestic level within Mexico, poverty and inequality can lead to similar dynamics, yielding a generalized perception among the poor or resource deprived that the existing social order or norms are illegitimate.

Finally, one last testable argument emerges from the conflict literature, namely, the role of uneven terrain. Fearon and Laitin (2003) first advanced the argument in a prominent piece, finding that mountainous terrain has a positive relationship with armed conflict. The logic of the argument highlighted the protective cover that uneven terrain afforded rebel groups, thus serving as geographic features that enhanced opportunities for violence. The empirical implication here is that we should see a positive relationship between areas of high variability in terrain and homicide rates. While all hypotheses extending from the conflict literature are provocative since we tend not to equate political violence with criminal violence,[1] this hypothesis regarding terrain unevenness is particularly appealing given its substantive spatial content. That is, where spatial hypotheses tend to examine horizontal geographic relationships, the terrain hypothesis suggests variation in the verticality of terrain may also matter.

SPILLOVER AND SOCIAL RELATIVITY

Following Yang et al. (2013), I seek to test whether the spatial dynamics in the data follow spillover or social relativity processes. As discussed by Yang et al., spillover effects emerged from the literature on regional and economic development, and are generally conceptualized, implicitly or explicitly, as a diffusion phenomenon (Rogers 1995; Capello 2009). In their study of the relationship between social capital and mortality, Yang et al. draw on these prior studies to propose that social capital can have a protective effect on mortality, and that if the social capital resources of a focal unit exceed the needs of that unit, i.e., if there is more social capital than the problem of mortality requires locally, then the excess resources will spread to nearby units and exert a similarly protective influence on mortality in those locations. Building on this perspective, I propose that predictors of homicide can also follow a similar process. For instance, assuming that population structure locally exerts an upward pressure on homicide locally, if population growth or density is large enough, the population pressure on violence may spread to nearby units.

Social relativity draws on social comparison work (Festinger 1954) to posit that, in estimating one's own condition or predicament, the absolute value of social or economic characteristics may matter, but the comparison of one's own position on these dimensions with

[1] Though this conceptual distinction is not straightforward upon close examination, as a wide range of research on crime and the (inherently political) nature of "deviant" behavior can attest.

the position of others may also determine whether the response to this condition is positive or negative. For instance, a person may be poor and may react negatively, becoming frustrated or depressed. However, if that person is surrounded by others who are even poorer, then the person may react positively. As discussed by Yang et al., and in contrast to the positive feedback of spatial spillovers, the social relativity perspective generates the possibility of negative feedback, i.e., of an unexpected reverse or “opposite” effect than that anticipated by theory.

The “opposite” or counterintuitive implications of the social relativity argument is especially compelling in the study of crime since it suggests specific spatial dynamics and identifies how conventional, accepted efforts to reduce crime in one area may backfire, resulting instead in even higher rates of crime. For instance, one community may see a benefit in reducing resource deprivation, improving incomes and overall economic wellbeing. However, as that happens in one particular community, neighboring communities may begin to perceive themselves less well in comparison to the first unit, resulting in higher crime in that unit. Notably, if the perception of resource deprivation worsens in the second unit, the first unit may also be targeted. This may happen for at least two reasons: (1) potential criminals may not want to commit the crime in their own community (or may recognize they are more likely to be caught), and (2) the perception is that higher resources, i.e., better targets, exist in the first unit.

In any case, the Durbin model and the rich interpretation afforded by the estimation and partitioning of direct and indirect effects enables the distinction between spillover and social relativity processes. The empirical implication is that, for any given explanatory variable, if direct effects (originating in focal unit) and indirect effects (originating in neighboring units of first or higher order) are both statistically significant and in the same direction (i.e., both negative or both positive), then a spillover process is present. Conversely, if both are statistically significant but in the opposite direction (i.e., one negative and one positive), then a social relativity process is present. If either is not significant, then neither spillover nor social relativity is present. The strengths of the Durbin model are discussed in detail in the methods section below.

METHODS AND DATA

The analysis adopts a subnational and spatial approach. As noted in the introduction, subnational research designs enhance analytic leverage by controlling for national-level characteristics (Snyder 2001). Further, the municipal level of analysis allows for the detection of spatial regimes that stretch across states and other administrative boundaries, demonstrating the cross-jurisdictional dimensions of an outcome of interest. Notably, despite drawing scholarly attention to the analytical leverage gained from "scaling down" (Snyder), and to the added leverage of multi-method research designs (Snyder and Moncada 2012), the subnational research agenda in comparative politics – especially quantitative variants – has largely ignored the structural dependence among observations. Indeed, it could be argued that spatial analysis is especially relevant to subnational research, where intra-national administrative boundaries are more porous that national ones.[2]

The core concerns of spatial analysis are spatial dependence and spatial heterogeneity (Anselin 1988). Spatial dependence occurs when units of analysis are connected in meaningful ways to other units of analysis, requiring analysts to operationalize that connectivity. Geographic contiguity, proximity, or accessibility are standard ways of conceptualizing this connectivity in geography and regional science. Therefore, the first null hypothesis to be examined in the spatial perspective is that of spatial randomness. If homicide rates are distributed randomly across

[2] See Harbers and Ingram (2013) for larger discussion of role of space in subnational research in comparative politics, and of the particular suitability of spatial analysis in subnational research.

Mexico's 2455 municipalities, then a conventional regression that assumes all observations are independently and identically distributed (i.e., i.i.d.) would be appropriate. If this distribution is not random, however, then the analysis calls for spatial econometric techniques.

Among econometric techniques, spatial analysts have typically focused on studying the autoregressive process in either the dependent variable (spatial lag models) or the error term (spatial error models). The spatial lag model is typically concerned with an "endogenous interaction relationship" (Manski 1993), where the outcome of interest in one unit is conditioned by the outcome in another unit, whereas Manski describes the spatial error model as a "correlated relationship", or what Franzese calls "common exposure", where the model identifies whether there is an unmeasured covariate that explains variation in an outcome of interest across a group of spatial units. Among these models, the study of diffusion has held the interest of social scientists as the spillover phenomenon is compelling. That is, the idea that an outcome in one place can spread or transfer to shape similar outcomes in other places has theoretical and substantive appeal. For instance, political scientists have studied the spread of democracy (Ward and Gleditsch). Others have examined the spatial error process in voter turnout (Darmofal 2008). Closer to the study of crime and violence, models have been employed to examine the spatial structure of homicide and other crime rates, including both spatial error and spatial lag models (e.g., Baller et al. 2001; Deane et al. 2008; Sparks 2011; Yang 2011).

In contrast to concerns with an autoregressive process in the dependent variable or error term, Manski identifies a third option that can underlie spatial autoregressive process, an "exogenous interaction relationship" (see also Yang et al. 2013). This last option proposes that the outcome of interest in a focal unit is explained in part by the determinants of that outcome in other units.

Formally, the general spatial model can be expressed in matrix notation as follows (Anselin 1988):

$$y = \rho Wy + X\beta + \varepsilon$$

$$\varepsilon = \lambda W\varepsilon + \mu \qquad (1)$$

In equation 1, β is a Kx1 vector of parameters associated with exogenous (i.e., non-lagged) variables X, which is an NxK matrix; ρ is the coefficient for the spatially lagged dependent variable; λ is the coefficient for the spatially lagged autoregressive structure of the disturbance ε, where μ is normally distributed around zero. W is an NxN row-standardized spatial weight matrix.

Assuming no spatial autoregressive effects, i.e., ρ=0 and λ=0, equation 1 reduces to the classic least-squares model in equation 2.

$$y = X\beta + \varepsilon \qquad (2)$$

Where there is an autoregressive process in the error term but no autoregressive process in the dependent variable, i.e., ρ=0, the model reduces to the spatial error model. Where there is an autoregressive process in the dependent variable but no autoregressive process in the error term, i.e., λ=0, the model reduces to the spatial lag model.

However, assuming the exogenous interaction process identified with the Durbin model, the specification is as follows, where θ is the coefficient for the lagged explanatory variables:

$$y = \rho Wy + X\beta + WX\theta + \varepsilon \qquad (3)$$

Equation 3 can be rewritten as follows, where I is the identity matrix:

$$y - \rho Wy = X\beta + WX\theta + \varepsilon$$

$$y(\mathrm{I} - \rho W) = X\beta + WX\theta + \varepsilon$$

$$y = (\mathrm{I} - \rho W)^{-1} X\beta + (\mathrm{I} - \rho W)^{-1} WX\theta + (\mathrm{I} - \rho W)^{-1}\varepsilon \quad (4)$$

From Equation 4, we can calculate the partial derivate of *y* with respect to any single independent variable in *X*, i.e., X_r, as:

$$\delta y/\delta X_{\mathrm{r}} = (\mathrm{I} - \rho W)^{-1}(I\beta + W\theta) \quad (5)$$

Equation 5 has several profitable empirical implications. First, focusing on the second part of the expression, i.e., $(I\beta + W\theta)$, $\delta y/\delta X_{\mathrm{r}}$ is a function of the coefficient (β) for the explanatory variable X_r within any one unit of interest, and also a function of the coefficient of the same explanatory in neighboring units ($W\theta$). These are the direct and indirect effects, respectively. Second, SDM estimates direct and indirect effects simultaneously, capturing steady-state feedback effects (LeSage and Pace 2010). Finally, since $(\mathrm{I} - \rho W)^{-1}$ can be expanded to capture powers of W (e.g., $I + \rho W + \rho^2 W^2 + \rho^3 W^3 + \ldots$), the model can estimate direct and indirect effects across higher orders of neighboring municipalities. The interpretation of the SDM results, therefore, can detect whether direct and indirect effects persist or decay across space. That is, whether immediate neighbors matter more than distant ones, whether one's neighbors' neighbors matter at all, and variation in these types of spatial dynamics across different explanatory variables, statistical significance, direction, and magnitude. In other words, the interpretation of SDM results can be very rich and nuanced.

Building on this discussion, the spatial Durbin model has several methodological and non-methodological advantages. Yang et al. (2013) highlight three primary methodological strengths unique to the Durbin model (citing LeSage and Pace 2009; Ellhorst 2010). First, spatial error and lag models restrict the magnitude of spatial effects for model estimation, while the Durbin model does not constrain the results in this way. Second, error and lag models can result in biased coefficients if the spatial interaction is misspecified, that is, if a "correlated relationship" is treated as a spatial lag process, or if an "endogenous interaction relationship" is treated as a spatial error process (see Yang et al.). Third, the spatial error and lag models do not capture the variation in direct and indirect effects, or the variation in these effects over higher orders of neighbors, as discussed above, neglecting the rich interpretations that are possible with SDM. In sum, the spatial Durbin model does not constrain the magnitude of spatial effects, is regarded as the "only means of producing unbiased coefficients" (Ellhorst 2010), "regardless of the true spatial process underlying the observed data" (Yang et al. 2013), and the interpretation of the model can shed light on the full variation of local and global effects. For these reasons, the spatial Durbin model constitutes the leading edge or state-of-the-art method in spatial analysis (Ellhorst 2010; Yang et al.). Turning to a non-methodological advantage, despite the strengths of the spatial Durbin model, I am unaware of any work that has applied a spatial Durbin model to the study of violence in Mexico, and only a single application of the model to the study of homicide in the U.S. (Ruther 2013). Thus, the Durbin analysis reported here leverages a novel method to contribute new findings to the literature on the origins of violence.

DATA

The dependent variable is from Mexico's national statistics office (INEGI), as organized by Trelles and Carreras (2012). The variable is logged to normalize its distribution. The municipal shapefile and additional georeferenced explanatory variables are from INEGI and the United Nations Development Program (UNDP) office in Mexico.[3] Specifically, the population structure component consists of population (logged) and population density (logged), both derived from 2010 population estimates and 2005 area (sq. km.) data from INEGI. Aspects of resource deprivation are captured by income per capita (in U.S. dollars, logged) and inequality (Gini coefficient), both of which are from the UNDP. Turnover data comes from Trelles and Carreras, along with the Participation Index, which is the number of votes cast in the two previous municipal elections divided over the number of registered voters (*votos emitidos/lista nominal*; Flamand, Martinez Pellégrini, and Camacho 2007). Finally, INEGI provides divorce rates (per 1000, logged) that capture family disruption, and altitude figures for localities within each municipality. The standard deviation of altitude within each municipality captures the unevenness of terrain.[4] Notably, Trelles and Carreras also use the population density measure as a proxy for urbanization; thus, taken together, the population variables could be used to capture an urban/rural divide. Table 1 reports descriptive statistics.

[Table 1 about here]

[3] The municipal shapefile and additional georeferenced census data are from INEGI (http://sc.inegi.org.mx/sistemas/cobdem; last accessed October 6, 2013). UNDP: www.undp.org.mx (last accessed October 6, 2013).

[4] This measure was inspired by Alberto Diaz-Cayeros.

Notably, there is frequently a tradeoff between the elimination of multicollinearity by using composite measures (e.g., principal components) of population structure, resource deprivation, and family disruption, as suggested by Land et al. (1990), and the more nuanced inferences made possible by individual covariates. However, this tradeoff can be avoided by selecting predictors that are not correlated with each other. For instance, recent analyses of crime (Sparks 2011) and mortality (Yang et al. 2013) have not used composite measures for key explanatory concepts, but rather have included the uncorrelated, individual covariates in their regressions. I do the same, having first confirmed the variables are not correlated, as well as confirming the absence of multicollinearity in the initial OLS model with the variance inflation factor (VIF). Generally, VIF values below 10 are acceptable, but a more rigorous cutoff is 4. All VIF values fall below 4.

EMPIRICAL STRATEGY

The analysis proceeds in three stages. I first conduct exploratory spatial analysis to identify any spatial regimes in the data. Here, Moran's *I* (Moran 1948) and a local version of the same statistic, local indicators of spatial autocorrelation (LISA) statistics (Anselin 1995), constitute the principal techniques. Second, spatial regressions examine the relationship among the dependent and independent variables while accounting for the dependent structure of the data. I then use the Aikake Information Criterion (Aikake 1974) and Lagrange Multiplier tests (Anselin 1988) to determine which model best fits the data and which model best accounts for spatial autocorrelation, respectively. Generally, lower AIC values identify the best models, and models with an AIC value more than 10 points lower than the comparison model should be preferred (Burnham and Anderson 2002, cited in Yang et al.). Lagrange Multiplier (LM) tests identify whether there is any remaining spatial autocorrelation among the residuals, and models with lower LM values that are not statistically significant should be preferred. Following these guidelines, post-estimation diagnostics of four separate models identify the spatial Durbin model as the one that best fits the data. Finally, given that coefficients of explanatory variables cannot be interpreted directly, I estimate direct and indirect effects, and partition these effects across higher-order neighbors to provide a more complete and nuanced explanation of the spatial dimension of homicide across Mexico's municipalities.

Throughout, a first-order queen contiguity matrix operationalizes the dependent structure of the data. Exploratory spatial analysis is conducted using GeoDa (v1.4.0; Anselin et al. 2006), and the spatial econometric analyses, including the use of the Markov Chain Monte Carlo method to calculate direct and indirect Durbin effects and partition results, are implemented in R (v3.0.2; R Core Team 2013), using the *spdep* package (Bivand 2013).

RESULTS

EXPLORATORY SPATIAL ANALYSIS

Exploratory techniques examine the first null hypothesis, namely, that there is no spatial dimension to the distribution of homicide rates across Mexico's municipalities. Stated otherwise, exploratory spatial analysis examines whether the distribution of homicide rates is spatially random. Exploratory spatial analysis, therefore, is "a critical first step for visualizing patterns in the data, identifying spatial clusters and spatial outliers, and diagnosing possible misspecification in analytic models" (Baller et al. 2001, 563). Maps are not a necessary step, but "[g]raphical displays provide an auxiliary method [to data tables] that may allow patterns to be discovered visually, quickly" (Ward and Gleditsch 2008, 11).

First, global and local tests of spatial autocorrelation capture the degree of overall structural dependence among units. Specifically, the global and local tests of spatial autocorrelation posit a null hypothesis of no spatial dependence among observations, i.e., spatial randomness, and then test whether this null hypothesis is supported. The global test is the global Moran's *I*, and examines whether there are any regular patterns among geographically connected units (Moran 1948; 1950a; 1950b; Cliff and Ord 1981). If there are no regular patterns of spatial association, the statistic is not significant. If there are significant spatial associations, the statistic can be positive or negative. A positive global Moran's *I* indicates that territorial units that are connected exhibit similar values on the outcome of interest; a negative result indicates territorial units that are connected have divergent or dissimilar values. The global Moran's I for homicide rates in 2010 is 0.10 ($p<.001$). The statistical significance allows us to confidently reject the null hypothesis of spatial randomness in the data. This suggests that standard regression techniques would not only be inappropriate, they would also overlook a key characteristic of the phenomenon.

Building on the discussion of global spatial autocorrelation, a local test for spatial dependence is the local Moran's I, or local indicator of spatial autocorrelation (*LISA*) (Anselin 1995). A LISA statistic provides information on the correlation on an outcome of interest among a focal unit *i* and the units to which *i* is connected, *j* (e.g., *i*'s neighbors, *j*), whether the association is positive (i.e., similar values) or negative (i.e., dissimilar values), and whether the association is statistically significant. Thus, LISA statistics serve to identify local clusters or spatial patterns of an outcome of interest. To be clear, while the global Moran's I may suggest that overall there is little spatial autocorrelation in the data, LISA values can identify smaller geographic areas where positive or negative clustering occurs.[5]

[5] The global Moran's I is the mean of all LISA values (Anselin 2005, 141).

Figure 2 reports a LISA cluster map showing the distribution of statistically significant clusters.[6] Blank areas are regions of spatial randomness in the distribution of violence, while colored areas are non-random spatial clusters. All cluster associations are significant at least at the .05 level.[7] Note also that the municipalities colored for significance constitute the core of spatial clusters. That is, the colored municipalities have a statistically significant relationship with the municipalities that border them, including those that are clear. Thus, the outer boundary of the cluster extends into the blank municipalities bordering the colored one, and the true size of the spatial cluster is larger than the colored cores (see, e.g., Anselin 2005, 146).

[Figure 2 about here]

The LISA cluster map also identifies the substantive content of those clusters. According to Anselin (2005, 140), this kind of map is "[a]rguably the most useful graph" in spatial analysis. Red identifies those municipalities with high levels of homicide that are surrounded by municipalities with similarly high levels of homicide (high-high). Blue identifies units with low homicide levels surrounded by units with similarly low levels (low-low). Light blue identifies those units with low levels of violence surrounded by units with high levels (low-high), while pink identifies those with high levels of homicides surround by units with low levels (high-low).[8]

[6] LISA significance map is omitted for sake of brevity.

[7] Generated in GeoDa (statistical significance based on permutation approach; 9999 permutations).

[8] This classification corresponds with the location of observations in a Moran scatterplot (Anselin 1996). If standardized LISA values are plotted along the x-axis, and the spatially weighted LISA values (LISAs for neighboring units) are plotted along the y-axis, the four resulting quadrants classify units as reflected in the cluster map (e.g., high-high in top-right quadrant, and low-low in bottom-left quadrant).

Figure 2 shows three spatial regimes that are analytically compelling (marked 1, 2, and 3 in the map). All three areas are high-violence spatial regimes. The first area straddles three states in northwestern Mexico: Sonora, Chihuahua, and Sinaloa. The second area sits at the intersection of three states in central Mexico: Nayarit, Zacatecas, and Jalisco. Lastly, the third area straddles another three states: Coahuila, Nuevo Leon, and Tamaulipas. Thus, these areas represent cross-jurisdictional clusters – spatial regimes that cross the boundaries of states. The policy implication is that any effort aimed at reducing violence in these areas must involve the collaboration of authorities from more than one state. The federal government is already heavily involved in enforcement actions, but if longer-term social policies are going to be developed to address the root causes of violence, then relevant actors across multiple subnational jurisdictions will need to collaborate and coordinate. Further, qualitative evidence that complements the spatial statistics shows that the drug trade has a strong presence in these regions. For instance, the second area is a marijuana cultivation zone that also sits at the territorial intersection of three drug trafficking organizations (Zamarroni Martinez 2013), validating the identification of this spatial regime, and signaling the kinds of state or federal policies that need to be coordinated. This particular finding also suggests that homicide rates in Mexico can serve as a proxy for measuring the drug trade, which is typically regarded as a "shadow economy" or "dark network" that resists measurement. Notably, unlike studies of homicide rates at the county level in the U.S. where the south emerges as a high-violence region and the northeast as a low-violence region (Land et al. 1990; Baller et al. 2001), there is no single region in Mexico that can be similarly singled out.

A key question is whether these spatial patterns are the product of (a) "correlated relationship" (Manski 1993), i.e., common exposure to a place-specific phenomenon (spatial error structure), (b) "endogenous interaction relationship", i.e., the diffusion of violence (spatial lag structure), or (c) "exogenous interaction relationship", i.e., a combination of the lagged outcome and lagged explanatory variables from neighboring units (spatial Durbin model). Different policy implications flow from common exposure, diffusion of the dependent variable, or the Durbin processes. Further, if common exposure is present, then the underlying, unmeasured factor generating the outcome still needs to be identified; if diffusion or a Durbin process is present, then the mechanism of diffusion still needs to be identified. The next section turns to spatial econometrics.

SPATIAL REGRESSION ANALYSIS

Table 2 reports the results for all spatial regressions. Four models examine the data: ordinary least-squares (OLS), a spatial error model (SEM), a spatial lag model (SLM), and a spatial Durbin model (SDM). Substantial residual spatial autocorrelation remains after estimating the basic OLS model (LM = 741.66, $p<0.001$), requiring a spatial regression. In conventional spatial analysis, Lagrange multiplier tests identify whether to pursue an error or lag specification. Here, both tests were significant, and neither robust test was significant at the .05 level (though the robust LM error test was more significant, at .10 level). Still, even if conventional model selection statistics clearly identified the superiority of an error specification or lag specification, or vice-versa, the Durbin model is preferred for the reasons stated previously. It should be noted that the interpretation of the coefficients in the SDM is not straightforward and is left for the following section on direct and indirect effects below. For now, two findings from Table 2 should be emphasized.

First, based on both statistical tests and theory, the Durbin model emerges as the best among all four. Looking at LM tests and model fit statistics, the spatial Durbin model receives the best evaluations. The LM tests suggested both common exposure (spatial error) and diffusion (spatial lag) processes are at work, and the LM tests of the OLS model and SEM indicate the presence of residual spatial autocorrelation. Additionally, as noted above, both the spatial error and spatial lag models fail to account for diffusion and feedback effects among explanatory variables. The spatial Durbin model addresses each of these shortcomings, and in a much richer fashion than either the error or lag specifications. Statistically, all of the spatial models have a lower AIC than the OLS model and this difference is either close to or greater than 10, indicating any spatial specification would be preferable to OLS. Considering the Wald, LR, and LM tests together, the values for each should follow a descending order (i.e., W>LR>LM; Anselin 2005). This is true for the lag and Durbin models, but not true for the error model. The LM test for the SLM and Durbin models show there is no remaining spatial autocorrelation, i.e., all spatial autocorrelation has been accounted for in both models. However, the AIC is lowest for the Durbin model (8770.70), suggesting this model fits the data best. To be sure, the significance of lambda (λ) in the spatial error model suggests the significance of unmeasured features and therefore the need to include omitted variables. However, the absence of spatial autocorrelation in the Durbin model and the inclusion of lagged explanatory variables that will offer richer explanations of any correlations caused by unmeasured variables offset any concerns about omitted variables. Finally, the SDM captures diffusion effects among the dependent variables *as well as* diffusion and feedback effects among the explanatory variables. For all of these reasons, I focus on the results of the Durbin model in the following section.

The second finding highlighted at this stage is the statistical significance of the lagged dependent variable (rho, ρ), which shows that patterns of homicide in one municipality can be explained by patterns of homicide in neighboring municipalities. Notably, the direction and magnitude of the coefficient across both the spatial lag and Durbin models is the same (.077 and .078), reinforcing the finding regarding the substantive effective of homicide rates in neighboring municipalities. This is strong evidence in favor of a spatial spillover effect for the dependent variable. Specifically, controlling for all other explanatory factors, a 1% increase in the homicide rates of neighboring municipalities translates into about a .1% increase in violence in a focal municipality.

[Table 2 about here]

DURBIN ESTIMATES: DIRECT, INDIRECT, AND PARTITIONED EFFECTS

Interpretation of the parameters in the Durbin model reported in Table 2 above is not the same as interpretation of parameters in OLS, or even in SEM and SLM. Indeed, interpretation of Durbin estimates can be mathematically complicated (Ellhorst 2010), but also much richer than in conventional spatial analysis (Yang et al. 2013). This is due to the fact that the model captures feedback effects among explanatory variables in neighboring units. "A change in the characteristics of neighboring regions can set in motion changes in the dependent variable that will impact the dependent variable in neighboring regions. These impacts will continue to diffuse through the system of regions" (LeSage and Pace 2010, 369). That is, the effect of an explanatory variable (X_{ir}) on y_i does not equal β_r, and the effect of the same explanatory variable in a neighboring unit (X_{jr}) on the outcome in the focal unit (y_i) does not equal zero. Rather, the *total effect* of an explanatory variable consists of the *direct effect* of the explanatory variable on y_i within the focal unit, plus the *indirect effect* of the explanatory variable (spillover effect) from neighboring units (LeSage and Pace 2010, 370). Moreover, these direct and indirect effects can vary over higher orders of neighbors, and are not the same for all units.

With this in mind, two effective ways to summarize direct and indirect effects are: (1) the average direct effect and average indirect effect across all units (Ellhorst 2010); and (2) partitioned direct and indirect effects across higher orders of neighbors, including the focal unit (zero-order neighbor) (LeSage and Pace 2009; 2010; Yang et al. 2013). Thus, I report average direct and indirect effects across all units, as well as partitioned direct and indirect effects across five orders of neighbors, showing how the magnitude and significance of these effects varies as we move out from the focal unit to more distant neighbors. The main findings demonstrate that: (1) among direct effects, education and uneven terrain have the anticipated effect, but several common predictors of violent crime have an unexpected relationship with homicide; (2) among indirect effects, only economic inactivity is significant and meaningfully affects homicide rates in any focal unit; (3) considering the combined direct and indirect effect of economic inactivity, a social relativity process (negative feedback) marks the relationship between economic inactivity and violence, while there are no spillover effects (positive feedbacks) among explanatory variables; and (4) as expected, direct effects are strongest in the focal units, indirect effects are strongest at the first order, and the decay of these effects is identifiable in partitioned results.

First, Table 3 reports average direct and indirect effects. Direct effects are those that originate in the focal unit and affect the dependent variable in the focal unit. For instance, consider a typical unit *i* with an explanatory variable X and outcome Y. The direct effect of X is the influence of X_i on Y_i. Indirect effects are those effects from neighboring units. For instance, consider a unit *j* with explanatory variable X and outcome Y. The indirect effect of X is the effect of X_j on Y_i. As Table 3 shows, direct and indirect effects can operate in the same direction (i.e., both positive or both negative) or in opposite directions, signaling either spillover or social relativity processes, respectively.

[Table 3 about here]

Among direct effects, population, income, and economic inactivity have significant and unexpected relationships with violence. Population and economic activity have unexpectedly negative effects, and income an unexpectedly positive effect. However, as expected, education has a significant (at. 10 level) and negative relationship with violence, and uneven terrain has a significant and positive effect on violence.

Second, the statistical significance of the indirect effect of economic inactivity demonstrates that this property of a particular municipality's neighbors exerts a meaningful effect on homicide rates within that municipality. Further, these indirect effects follow the theoretically expected relationships more than direct effects. Specifically, economic inactivity in a focal unit's neighbors exerts a positive influence on violence in said focal unit. That is, as unemployment increases and more people fall out of the workforce in nearby communities, homicide rates increase in a focal unit. While this result contrasts with the finding regarding direct effects here and with that of Land et al. (1992) and Baller et al. (2001) regarding economic inactivity in the U.S., the result does follow the more conventional theoretical expectation in the literature on economic activity and crime. Moreover, the opposite relationship between direct and indirect effects suggests a social relativity process underlying the economics of violence.

Partitioned Effects

Following Yang et al. (2013), while the direct and indirect effects highlight whether spatial spillover or social relativity processes are at work, partitioning these effects helps answer how important an immediate neighbor is versus more distant neighbors. To this end, Table 5 reports partitioned direct and indirect effects.

To be sure, the interpretation of these partitioned results is not straightforward, so two clarifying notes are in order. First, the interpretation of direct effects beyond the zero order may seem inappropriate. That is, why would there be within-unit effects beyond the focal unit of interest? Are these not more properly considered indirect effects? The answer to this question goes back to the nature of the Durbin model and the fact that the model captures a steady state of feedback effects among neighboring units. Thus, the intuition behind direct effects beyond the zero order is that a change in X*i* can affect X*j* (e.g., first-order neighbor), which can then be reflected back as an influence on Y*i*. This occurs across all higher orders of neighbors. Second, the interpretation of indirect effects below the first order may seem inappropriate. That is, why would there be indirect effects within the focal unit of interest, i.e., below the first-order neighbor? Are these not more properly considered direct effects? Again, the answer to this question resides in the feedback processes captured by the Durbin model. The intuition behind indirect effects at the zero order is that this effect captures all the indirect effects from the first-order neighbor and above. Similarly, the indirect effects at the first order (W_1) captures all the indirect effects of the second-order neighbor and up, and so on.[9] One last clarification is that since the spatially lagged explanatory variables ($\boldsymbol{X\beta}$) are significant, the direct effects at the first order will not be zero and the indirect effects at the zero order will not be zero (Jensen and Lacombe 2012; cited in Yang et al. 2013).

With this in mind, the results from Table 5 show that direct effects are rarely significant beyond W_0, essentially disappearing beyond the first-order neighbors, and that a similar process of decay occurs with indirect effects. Comparing the zero-order direct effects with the total direct effects reported in Table 3 above shows that the focal unit contributes most of the effect. For instance, the focal unit contributes 99.6% (.228/.229) of the direct effect for population. Similarly, the indirect effect of the first-order neighbor (represented by the indirect effect at W_0) contributes

[9] I am grateful to Tse-Chuan Yang for conversations clarifying the intuitions reported here.

most of the effect. For example, the first-order indirect effect of PNEA accounts for 99.8% (5.952/5.961) of the effect. The graphs in Appendix A visualize how direct and indirect effects decay across higher orders of neighbors.

[Table 5 about here]

DISCUSSION AND CONCLUSIONS

Examining the spatial dependence of homicide rates, this paper offers the first spatial Durbin analysis of violent crime across Mexico's municipalities. The novel methodological approach builds on existing sociological, political science, and demographic research to offer new insights regarding the origins of violence in a key neighbor to the U.S. and one of the largest democracies and markets in Latin America.

The analysis yields four principal findings. First, violence is not spatially random across Mexico's 2455 municipalities. Spatial regimes exist throughout Mexico. Particularly compelling are spatial regimes of violence that straddle multiple state boundaries. For instance, a cluster of high homicide rates straddles the boundaries of three states in central Mexico – Jalisco, Nayarit, and Zacatecas – suggesting the need for state and federal authorities to coordinate and collaborate on social, economic, and law enforcement policies. Qualitative evidence that complements the spatial statistics shows that this particular region is a marijuana cultivation area that also sits at the territorial intersection of three drug trafficking organizations (Zamarroni Martinez 2013), validating the identification of this spatial regime, and signaling the kinds of state or federal policies that need to be coordinated. This particular finding also suggests that homicide rates in Mexico can serve as a proxy for measuring the otherwise difficult-to-measure drug trade.

The cross-jurisdictional spatial regimes also highlight challenges to developing effective crime-reduction policies. That is, these intermediate regions of violence – above the municipal level, below the state level, and crossing state boundaries – demand cooperation, coordination, and collaboration among two or more states, and perhaps the federal government. This kind of inter-governmental policymaking is not always easy, especially when it involves both law enforcement and socio-economic policy issues.

Second, a key finding highlights the spillover of the dependent variable. That is, an increase in the homicide rate in one municipality exerts an upward pressure on the homicide rate in neighboring municipalities. This spillover effect suggests that neighboring communities have a shared interest in reducing each other's levels of violence. Thus, again, neighboring communities should develop regional policies to reduce and prevent violence. The findings regarding the explanatory variables, especially education and economic inactivity, help us understand how to do this.

A key strength of the Durbin model is reflected in the rich interpretation that is possible with the decomposition of direct and indirect effects. Thus, a third finding relates to the interpretation of spillover or social relativity processes using the direct and indirect effects, and a fourth finding relates to the ability to detect the persistence, decay, or reversal of effects across higher orders of neighbors. The decomposed and partitioned direct and indirect effects run counter to much of the literature on homicide rates in the U.S.: population, population density, income, and inequality have an unexpected negative relationship with homicide. I interpret the population and density findings to suggest that highly populated areas have less violence than more rural, less populated areas. Further, this is primarily a direct effect, and the effect does not persist across higher orders of neighbors, suggesting the current homicide phenomenon in Mexico is occurring outside large cities, but in adjoining areas not far from these cities.

Regarding income, an increase in local, within-unit income is unexpectedly associated with higher levels of violence, but the partitioned indirect effects show that an income increase among the contiguous neighbors (reflected at W_0) leads to a reduction in violence in the focal unit (significant at .10 level).[10] The opposite direction of the low-order direct and indirect effect suggest a social relativity process, namely, that a within-unit increase in income may draw offenders from surrounding communities. Thus, when income increases in surrounding communities, violence decreases in the central unit. Again, the policy implication is that neighboring communities have a shared interest in each other's economic growth. More specifically, neighboring communities have a mutual interest in growing economically, and in doing so at relatively the same rate in order to reduce perceived spatial inequalities.

The findings regarding economic inactivity (PNEA) support this inference. Indeed, the evidence is stronger with PNEA for a social relativity process in which homicide is being committed in a central unit by those in surrounding units propelled by economic factors. Specifically, an increase in economic inactivity (e.g., unemployment) decreases local homicide rates. This much is consistent with findings in the U.S., where scholars argue that economic inactivity may constrain the circulation of people, thus affording fewer targets for violent crime (e.g., Baller et al.). However, the indirect effect of the first-order neighbor (reflected at W_0) is in the opposite direction, significant, and of substantial magnitude. Again, this social relativity process suggests that deteriorating economic conditions in one's neighboring community generate higher violence in one's own community. Thus, neighboring communities should work to develop economically at similar rates.

[10] The direction of the effect reverses again at the next order of neighbors and is statistically significant, but the magnitude of this effect is much smaller.

Alongside these regional or neighborhood effects, education and uneven terrain are significant predictors of violence. Education has the expected negative relationship with violence, though this finding is only significant at the .10 level. Further, education only exerts its protective effect within a particular municipality, i.e., education only has a direct effect on violence and no indirect effects. Thus, the education-violence relationship is more of a local phenomenon, and the policy implication is that education-attainment programs can be narrowly targeted within municipalities. Finally, uneven terrain has the expected positive relationship with violence. This finding brings the armed conflict and criminology literatures into closer conversation, but as with the armed conflict research the policy implication is unclear. Is this variable capturing weak state capacity and enforcement? Or are rural, mountainous regions areas of higher drug production, and therefore, all else being equal, areas of more concentrated violence? The underlying mechanism is unclear, and deserves more attention in future research.

Overall, the non-random distribution of violence across space, the diffusion of violence, the direct and indirect effects of explanatory variables, and the quick decay or reversal of these effects across higher orders of neighbors increase our understanding of the origins of violence in Mexico. The rich interpretations of direct and indirect effects across higher orders of neighbors is only possible with the spatial Durbin model, so the analysis also demonstrates the promise of continuing to apply this technique in future studies of violence, over time and across different types of violence.

In conclusion, the findings highlight the need for a mixed approach of policies that are (a) aimed at a more regional level encompasses relevant sets of municipalities, even if these municipalities cross major jurisdictional boundaries, e.g., state lines, and (b) targeted at specific municipalities and (b). First, three findings highlight the need for violence-reduction policies that adopt a regional approach: cross-jurisdictional spatial regimes, the lag effect of violence, and the indirect effects of PNEA. Policymakers can use the tools of spatial analysis or other regional knowledge to identify sets of municipalities that are more connected to each other than to other municipalities, and design policies that cover the entire set of relevant communities. These violence-reduction policies should emphasize economic development at an intermediate, regional level of subnational government – below states and above municipalities – again, even if those regions cross state or other traditional jurisdictional boundaries. This may be the main the challenge to this approach, since cross-jurisdictional cooperation or collaboration may be difficult. Second, the findings regarding the local, intra-municipality effect of education call for the promotion of education policies targeted at individual municipalities. Combined, the regional economic policies and local education policies constitute what I call a "local-schools/regional-economy" approach to violence prevention and reduction.

I imagine that these policy recommendations will be uncontroversial to some urban or regional planners, and perhaps even unsurprising. However, given the emphasis on formal institutional reforms of law enforcement and the judicial sector, the neglect of the deep literatures in sociology and criminology that addresses why crime occurs in the first place is startling in places like Mexico. For instance, millions have been invested in countless waves of police reform over the last three decades (e.g., Sabet 2012), and millions more have been invested in a prominent criminal procedure reform since 2008 that is primarily geared towards re-designing the way the justice system operates – including judges, prosecutors, public defenders, and police (Ingram and Shirk 2012). Only passing attention has been given to the broader social and economic conditions that underlie why criminal behavior occurs in the first place, before people get involved in the justice system. To be sure, there are encouraging developments in the recent emphasis on constructing "resilient communities" in the new "Pillar IV" of the Merida Initiative (e.g., DOS 2011; Negroponte 2011). The findings here suggest this new emphasis is on the right track and that policymakers should increasingly turn their attention to the social, political, and economic literatures addressing root causes of violence, but do so with a particular spatial process in mind for different policy areas, namely, the social relativity process underlying the opposing direct and indirect effects of economic inactivity, and the more territorially-bounded, direct effects of education. In terms of national or international grant competitions or other opportunities for funding, the findings suggest funders should reward programs and policies addressing these regional and local dynamics, especially those programs and policies that include collaborative, cross-jurisdictional efforts to address regional, economic sources of violence like regional pockets of unemployment, low labor force participation, or other forms of economic inactivity alongside targets policies to improve local educational attainment.

References

Anselin, Luc. 1988. “Lagrange multiplier test diagnostics for spatial dependence and spatial Heterogeneity.” *Geographical Analysis* 20: 1-17.

Anselin, Luc. 1995. “Local indicators of spatial association – LISA.” *Geographical Analysis* 27: 93-115.

Anselin, Luc, and A.K. Bera. 1998. “Spatial dependence in linear regression models with an introduction to spatial econometrics.” In A. Ullah, and D. E. A. Giles, eds. *Handbook of applied economic statistics*. New York: Marcel Dekker.

Anselin, Luc. 2005. *Exploring Spatial Data with GeoDa: A Workbook*. March 6, 2005. Available at: https://geodacenter.asu.edu/og_tutorials (last accessed April 2, 2013).

Anselin, Luc, Ibnu Syabri and Youngihn Kho. 2006. “GeoDa: An Introduction to Spatial Data Analysis.” *Geographical Analysis* 38 (1), 5-22.

Assunção, R. and Reis, E. A. 1999. “A new proposal to adjust Moran’s I for population density.” *Statistics in Medicine* 18: 2147–2161.

Bailey, John, and Lucía Dammert. 2006. “Public Security and Police Reform in the Americas.” In Bailey and Dammert, eds. *Public Security and Police Reform in the Americas*. Pittsburgh: University of Pittsburgh Press.

Baller, Robert D., Luc Anselin, Steven F. Messner, Glenn Deane, Darnell F. Hawkins. 2001. “Structural Covariates of U.S. Homicide Rates: Incorporating Spatial Effects.” *Criminology* 39(3): 561-590.

Beck, Nathaniel, Kristian Skrede Gleditsch, and Kyle Beardsley. 2006. “Space Is More Than Geography: Using Spatial Econometrics in the Study of Political Economy.” *International Studies Quarterly* 50(1): 27-44.

Beck, Nathaniel L. and Jonathan N. Katz. 1996. “Nuisance vs. Substance: Specifying and Estimating Time-Series-Cross-Section Models.” *Political Analysis* 6:1–36.

Besag, Julian E. 1972. “Nearest-neighbour Systems and the Auto-logistic Model for Binary Data.” *Journal of the Royal Statistical Society*, Series B, Methodological p. 75.

Besag, Julian E. 1974. “Spatial Interaction and the Statistical Analysis of Lattice Systems (with Discussion).” *Journal of the Royal Statistical Society*, Series B, Methodological pp. 192–225.

Bivand, Roger. 2002. “Spatial Econometrics Functions in R: Classes and Methods.” *Journal of Geographical Systems* 4(4): 405-421.

Bivand, Roger, Edzer Pebesma, and Virgilio Gomez-Rubio. 2007. *Applied Spatial Data Analysis with R*. New York: Springer.

Bivand, Roger. 2013. “Spatial dependence: weighting schemes, statistics and models.” Version 0.5-65 (2013-09-04). Available at: http://cran.r-project.org/web/packages/spdep/index.html

Calvo, Ernesto, and Marcelo Escolar. 2003. “The local voter: A geographically weighted approach to ecological inference.” *American Journal of Political Science* 47(1): 189–204.

Charlton, Martin, and A. Stewart Fotheringham. 2009. “Geographically Weighted Regression: White Paper.” National Centre for Geocomputation, National University of Ireland Maynooth. Available at: http://ncg.nuim.ie/ncg/gwr/GWR_WhitePaper.pdf (last viewed March 30, 2013).

Cliff, A.D., and J.K. Ord. 1981. *Spatial Processes: Models and Applications*. London: Pion Ltd.

Collier, Paul, and Anke Hoeffler. 2004. “Greed and grievance in civil war.” *Oxford Economic Papers* 56: 563-595.

Darmofal, David. 2006. “The political geography of macro-level turnout in American political development.” *Political Geography* 25: 123-150.

Department of State (DOS). 2011. “The Merida Initiative: Expanding the U.S./Mexico Partnership.” U.S. Department of State, Bureau of Public Affairs. Available at: http://www.state.gov/documents/organization/158009.pdf

Ellhorst, J. Paul. 2010. “Applied Spatial Econometrics: Raising the Bar.” *Spatial Economic Analysis* 5(1): 9-28.

Federal Bureau of Investigation (FBI). 2011. “Crime in the U.S., 2010: Murder”. Available at: http://www.fbi.gov/about-us/cjis/ucr/crime-in-the-u.s/2010/crime-in-the-u.s.-2010/violent-crime/murdermain).

Flamand, Laura, Sárah Martinez Pellégrini, and Ofelia Camacho. 2007. “Metodología de Cálculo: Índice de Desarrollo Municipal Básico (IDMb).” Colegio de la Frontera Norte (Feb.)

Fotheringham, A. Stewart, Chris Brunsdon, and Martin Charlton. 2002. *Geographically Weighted Regression: the analysis of spatially varying relationships*. Chichester, England: Wiley and Sons.

Gleditsch, Kristian Skrede, and Michael D. Ward. 2005. "Visualization in International Relations." In *New Directions for International Relations: Confronting the Method-of-Analysis Problem*, ed. Alex Mintz and Bruce Russett. Lanham: Lexington Books, 65-91.

Gleditsch, Kristian Skrede, and Nils B. Weidmann. 2012. "Richardson in the Information Age: Geographic Information Systems and Spatial Data in International Studies." *Annual Review of Political Science* 15, 1: 461-81.

Gleditsch, Kristian and Michael Ward. 2000. “War and Peace in Time and Space: The Role of Democratization.” *International Studies Quarterly* 44(1):1–29.

Goodchild, Michael F., Luc Anselin, Richard P. Applebaum, and Barbara Herr Harthorn. 2000. “Towards Spatially Integrated Social Science.” *International Regional Science Review* 23(2): 139-159.

Goodchild, Michael F., Donald G. Janelle. 2010. “Toward critical spatial thinking in the social sciences and humanities.” *GeoJournal* 75: 3-13.

Griffith, Daniel A. 1987. *Spatial Autocorrelation: A Primer*. Washington, D.C.: Association of American Geographers.

Franzese, Robert Jr., and Jude C. Hays. 2008a. “Spatial Interdependence in Comparative Politics: Substance, Theory, Empirics, Substance.” *Comparative Political Studies* 41(4/5): 742-780.

Franzese, Robert Jr., and Jude C. Hays. 2008b. “Empirical Models of Spatial Interdependence.” In Janet Box-Steffensmeier, Henry E. Brady, and David Collier, eds. *The Oxford Handbook of Political Methodology* . Oxford: Oxford University Press, pp. 570-604.

Ingram, Matthew C., and David A. Shirk. 2012. "Building Institutional Capacity in Mexico's Criminal Justice System." In George Philip and Susana Berruecos, eds. *Mexico’s Struggle for Public Security: Organized Crime and State Responses*. London: Palgrave MacMillan.

Jensen, C.D., and D.J. Lacombe. 2012. “A note on partitioning effects estimates over space.” *Letters in Spatial Resource Sciences* 5(1): 47-53.

King, Gary. 1997. *A Solution to the Ecological Inference Problem*. Princeton: Princeton University Press.

LeSage James P., and R. Kelley Pace. 2009. *Introduction to spatial econometrics*. Taylor & Francis: Boca Raton, FL.

LeSage James P., and R. Kelley Pace. 2010. “Spatial Econometric Models.” In Manred M. Fischer and Arthur Getis, eds. *Handbook of Applied Spatial Analysis: Software Tools, Methods, and Applications*. Berlin: Springer, pp: 355-376.

Mainwaring, Scott, Timothy R. Scully, and Jorge Vargas Cullell. 2010. “Measuring Success in Democratic Governance.” In Mainwaring and Scully, eds. *Democratic Governance in Latin America*. Stanford: Stanford University Press.

Manski, C.F. 1993. “Identification of endogenous social effects: The reflection problem.” *The Review of Economic Studies* 60: 531-542.

Messner, Steven F., Luc Anselin, Robert D. Baller, Darnell F. Hawkins, Glenn Deane, and S.E. Tolnay. 1999. "The spatial patterning of county homicide rates: An application of exploratory spatial data analysis." *Journal of Quantitative Criminology* 15: 423-450.

Messner, Steven F., Raymond H.C. Teske, Jr., Robert D. Baller, and Helmut Thome. 2011. "Structural Covariates of Violent Crime Rates in Germany: Exploratory Spatial Analyses of Kreise." *Justice Quarterly*, DOI:10.1080/07418825.2011.645862

Molzahn, Cory, Viridiana Rios, and David Shirk. 2012. *Drug Violence in Mexico: Data and Analysis through 2011*. Special Report. Trans-Border Institute, University of San Diego.

Moncada, Eduardo, and Richard Snyder. 2012. "Subnational Comparative Research on Democracy: Taking Stock and Looking Forward." *Newsletter of the Comparative Democratization Section of the American Political Science Association,* 10, 1: 1-9.

Moran, Patrick Allen Pierce. 1948. "The interpretation of statistical maps." *Journal of the Royal Statistical Society* B, 10, 243-251.

Moran, Patrick Allen Pierce. 1950a. "Notes on Continuous Stochastic Phenomena." *Biometrika* 37: 17-23.

Moran, Patrick Allen Pierce. 1950b. "A Test for Serial Independence of Residuals." *Biometrika* 37: 178-181.

Negroponte, Diana. 2011. "Pillar IV of 'Beyond Merida': Addressing the Socio-Economic Causes of Drug Related Crime and Violence in Mexico." Working Paper Series on U.S.-Mexico Security Cooperation. Mexico Institute, Woodrow Wilson International Center for Scholars, Washington, D.C. Available at: http://www.wilsoncenter.org/staff/diana-negroponte

Öcal, Nadir, and Jülide Yildirim. 2010. "Regional effects of terrorism on economic growth in Turkey: A geographically weighted regression approach." *Journal of Peace Research* 47(4): 477–489.

Prillaman, William C. 2003. "Crime, Democracy, and Development in Latin America." Policy Papers on the Americas Volume XIV, Study 6. Center for Strategic and International Studies (CSIS), Washington, D.C.

Putnam, Robert. 1994. *Making Democracy Work*. Princeton: Princeton University Press.

R Core Team. 2013. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. Available at: http://www.R-project.org/.

Ruther, Matt. 2013. "The effect of growth in foreign born population share on county homicide rates: A spatial panel approach." *Papers in Regional Science*. Early online publication (June 24): doi:10.1111/pirs.12045.

Snyder, Richard. 2001. "Scaling Down: The Subnational Comparative Method." *Studies in Comparative International Development* 36, 1: 93-110.

Snyder, Richard, and Angelica Duran-Martinez. 2009. "Does Illegality Breed Violence? Drug Trafficking and State-Sponsored Protection Rackets." *Crime, Law and Social Change* 52, 3: 253-73.

Snyder, Richard, and Eduardo Moncada. 2012. " Subnational Comparative Research on Democracy: Taking Stock and Looking Forward." *APSA-CD, Comparative Democratization* (Jan.) 10(1): 1, 4-9.

Tam Cho, Wendy K., and James Gimpel. 2012. "Geographic Information Systems and the Spatial Dimension of American Politics." *Annual Review of Political Science* 15: 443-460.

Trelles, Alejandro, and Miguel Carreras. 2012. "Bullets and Votes: Violence and Electoral Participation in Mexico." *Journal of Politics in Latin America* 4(2): 89-123.

Ward, Michael, and Kristian Skrede Gleditsch. 2008. *Spatial Regression Models*. Thousand Oaks, CA: SAGE Publications.

Yang, Tse-Chuan, Aggie J. Noah, and Carla Shoff. 2013. "Exploring Geographic Variation in U.S. Mortality Rates Using a Spatial Durbin Approach." *Population, Space, and Place*. Advance online publication. DOI: 10.1002/psp.1809

Zhukov, Yuri M. 2012. "Roads and the diffusion of insurgent violence: The logistics of conflict in Russia's North Caucasus." *Political Geography* 31: 144-156.

Table 1. Descriptive Statistics

Variable	N	Mean	S.D.	Min	Max	VIF
Homicide rate (per 1000)	2455	0.41	1.55	0.00	38.79	--
Homicide rate (logged)	2455	-2.20	1.54	-5.00	3.66	--
Population (logged)	2455	9.37	1.67	0.00	14.41	3.49
Population density (logged)	2455	3.92	1.69	-1.94	9.77	1.75
Median age	2455	24.95	4.61	14	45	1.92
Income/cap (logged)	2455	8.55	0.73	0.00	10.43	2.45
PNEA (%)	2455	0.40	0.05	0.20	0.74	1.59
Gini (2005)	2455	0.40	0.06	0.00	0.60	1.57
Education years (mean)	2455	6.65	1.53	2.03	13.52	2.13
Divorce rate (ln)	2455	-0.50	1.00	-4.80	2.79	1.13
Turnover (2006-2009)	2455	0.49	0.50	0.00	1.00	1.14
Participation index	2455	0.61	0.13	0.00	0.93	1.29
Altitude (std. dev., ln)	2455	4.33	1.63	-2.30	6.70	1.26

Table 2. Spatial Regression Results

	OLS	SEM	SLM	Durbin (SDM)	
DV: homicide rate (per 1000, logged)					
	Coef.	Coef.	Coef.	Coef.	Lag
Population	-0.260***	-0.264***	-0.253***	-0.280***	0.080
Density	-0.115***	-0.113***	-0.106***	-0.071	-0.044
Median age	-0.014	-0.014	-0.014	-0.009	-0.016
Income	0.665***	0.669***	0.648***	0.645***	-0.080
PNEA	-3.172***	-3.440***	-3.218***	-4.948***	5.906***
Inequality	-1.588**	-1.570*	-1.467*	-1.244	-0.233
Education	-0.062*	-0.065*	-0.064*	-0.075[Ŧ]	0.083
Divorce rate	0.025	0.023	0.022	0.007	0.016
Turnover	-0.068	-0.060	-0.061	-0.026	-0.175
Participation	-0.085	-0.039	-0.055	0.276	-0.643
Uneven terrain	0.112***	0.111***	0.107***	0.090**	0.018
(Intercept)	-2.724***	-2.637***	-2.517***	-3.890***	
Lambda (λ)		0.089**			
Rho (ρ)			0.077***	0.078*	
N	2455	2455	2455	2455	
Wald		3.14	6.271	6.039	
LR test		7.106	5.839	5.582	
AIC	8781.60	8776.50	8777.80	8770.70	
L-L		-4374.26	-4374.893	-4360.333	
LM test	741.66	NA	1.360	0.370	
Pr(LM)			0.243	0.543	

* p<.05, ** p<.01, *** p>.001, [Ŧ] p<.10

Table 3. Direct and Indirect Effects

	Direct	Indirect	Total
Population	-0.280***	0.063	-0.217***
Density	-0.072	-0.053	-0.125***
Median age	-0.010	-0.017	-0.027
Income	0.644***	-0.032	0.613***
PNEA	-4.871***	5.910***	1.039
Inequality	-1.249	-0.353	-1.602^{Ŧ}
Education	-0.074^{Ŧ}	0.083	0.009
Divorce rate	0.008	0.018	0.026
Turnover	-0.029	-0.190	-0.218
Participation	0.267	-0.665	-0.398
Uneven terrain	0.091**	0.027	0.118***

*** $p<.001$, ** $p<.01$, * $p<.05$, ^{Ŧ} $p<.10$

Table 4. Overview of Spillover and Social Relativity Arguments

	Spatial Spillover (same direction)	**Social Relativity (opposite direction)**
Population (ln)	NS	NS
Density (ln)	NS	NS
Income/Cap (ln)	NS	NS
PNEA (%)	NS	**Yes**
Gini	NS	NS
Divorce rate (ln)	NS	NS
Turnover	NS	NS
Participation	NS	NS
Altitude (s.d., ln)	NS	NS

Table 5. Partitioned Direct and Indirect Effects

	Direct					Indirect				
	W_0	**W_1**	**W_2**	**W_3**	**W_4**	**W_0**	**W_1**	**W_2**	**W_3**	**W_4**
Population (ln)	-0.280***	0.001	0.000	0.000	0.000	0.080	-0.017*	-0.001	0.000	0.000
Density (ln)	-0.071	-0.001	0.000	0.000	0.000	-0.044	-0.008*	-0.001	0.000	0.000
Median age	-0.009	0.000	0.000	0.000	0.000	-0.016	-0.002	0.000	0.000	0.000
Income/Cap (ln)	0.645***	-0.001	0.001	0.000	0.000	-0.080	0.045*	0.003	0.000	0.000
PNEA (%)	-4.948***	0.080*	-0.003	0.000	0.000	5.906*	-0.006	0.009	0.000	0.000
Gini	-1.244	-0.003	-0.001	0.000	0.000	-0.233	-0.112	-0.008	-0.001	0.000
Education	-0.075[Ŧ]	0.001	0.000	0.000	0.000	0.083	0.000	0.000	0.000	0.000
Divorce rate (ln)	0.007	0.000	0.000	0.000	0.000	0.016	0.002	0.000	0.000	0.000
Turnover	-0.026	-0.002	0.000	0.000	0.000	-0.175	-0.013	-0.001	0.000	0.000
Participation	0.276	-0.009	0.000	0.000	0.000	-0.643	-0.020	-0.002	0.000	0.000
Uneven terrain	0.090**	0.000	0.000	0.000	0.000	0.018	0.008*	0.001	0.000	0.000

*** p<.001, ** p<.01, * p<.05, [Ŧ] p< .10

Figure 1. Decile map of 2010 homicides rates across Mexico's 2455 municipalities.

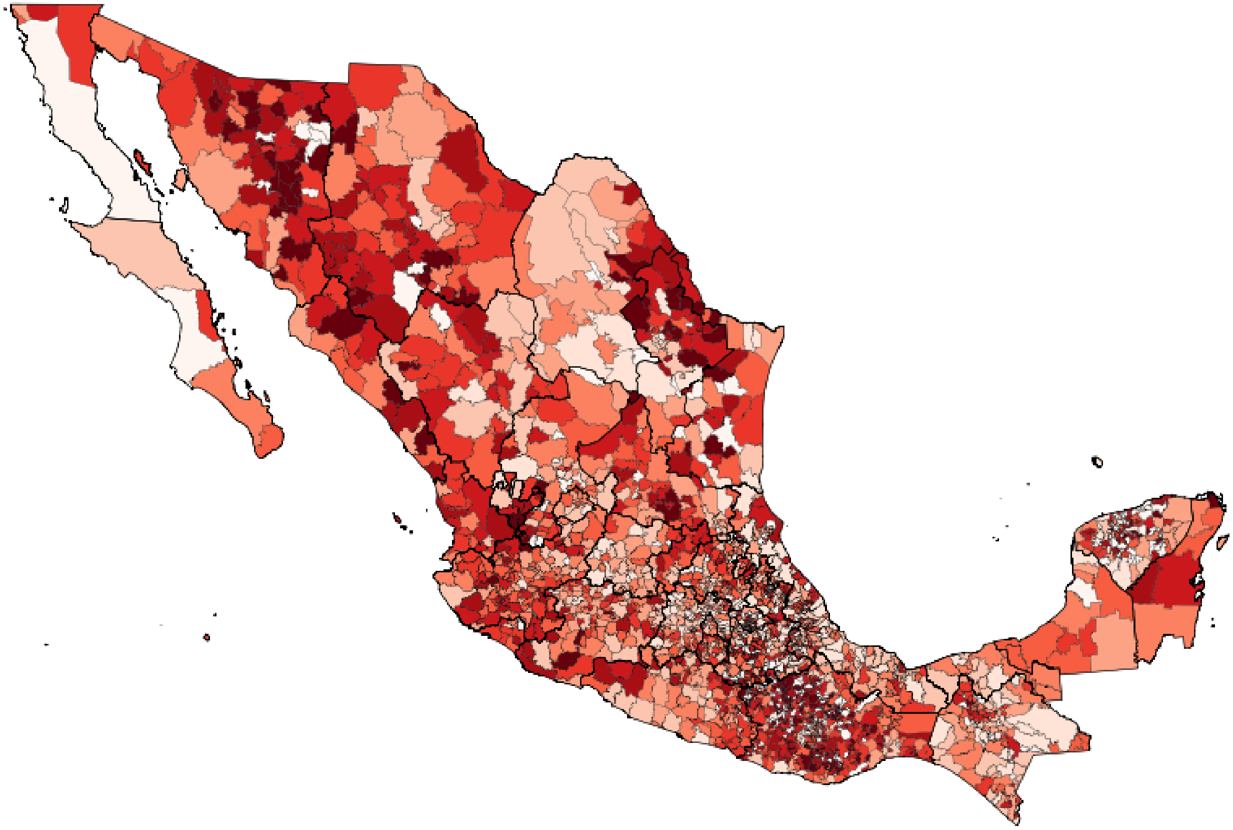
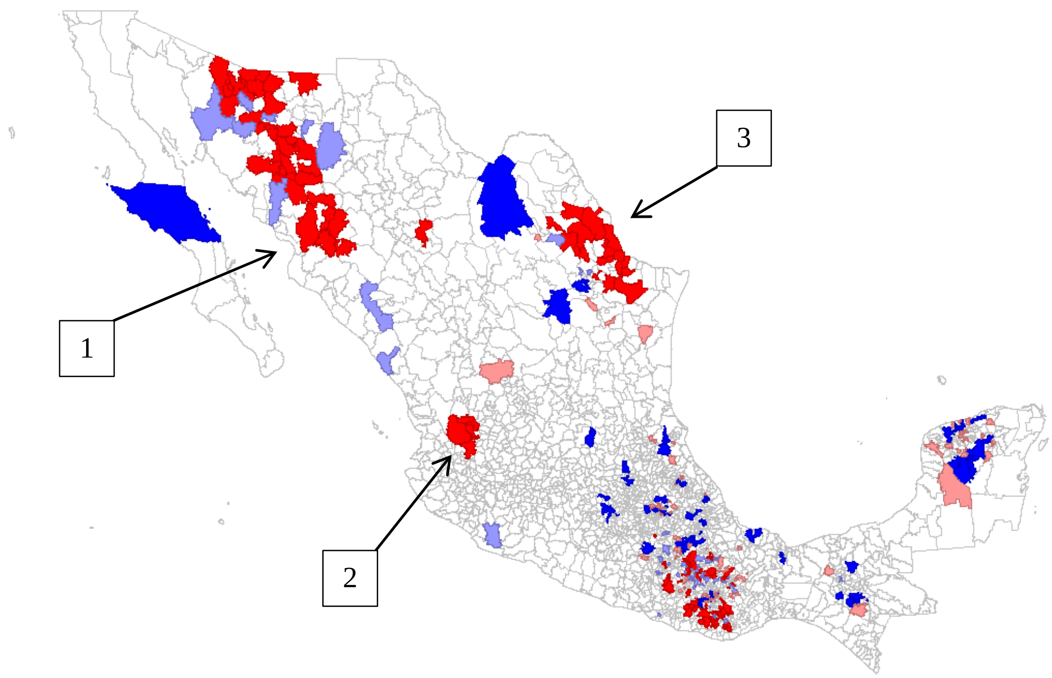


Figure 2. LISA cluster map of homicide rates (logged).



Appendix A. Graphs of Partitioned Direct and Indirect Effects

Figure A1. Direct (left) and Indirect (right) Effects for Population and Population Density

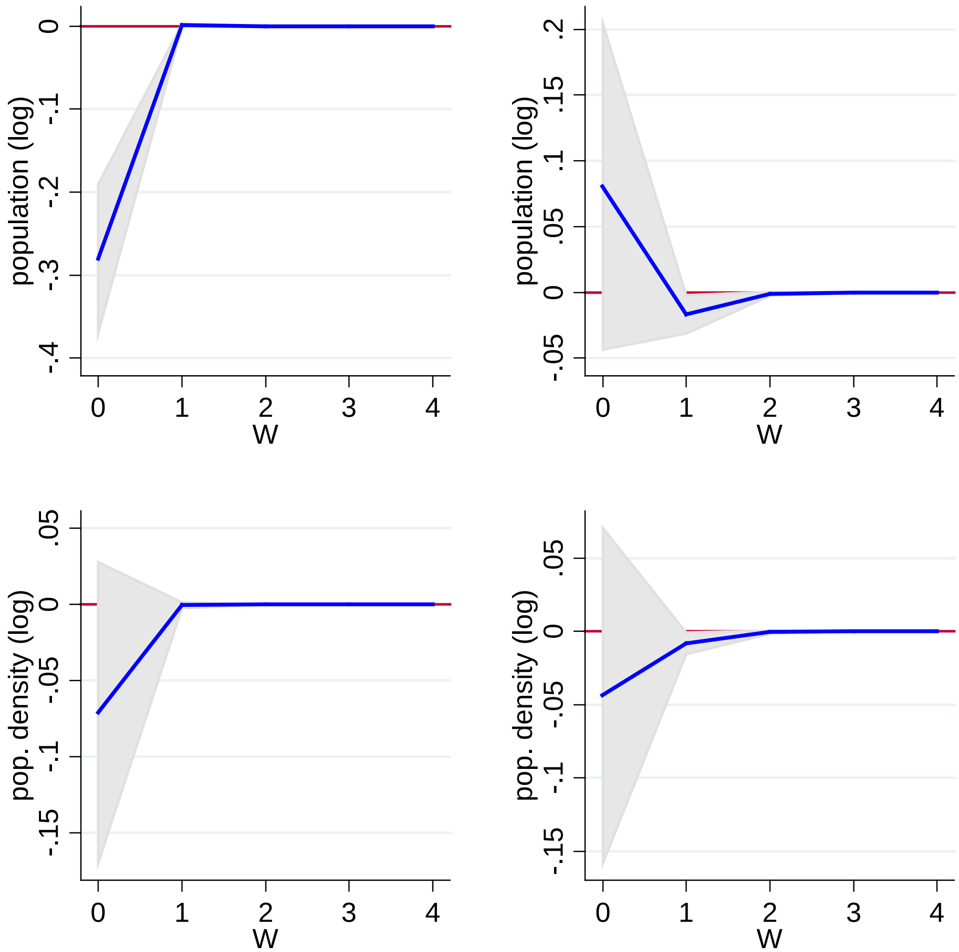


Figure A2. Direct and Indirect Effects of Age and Education

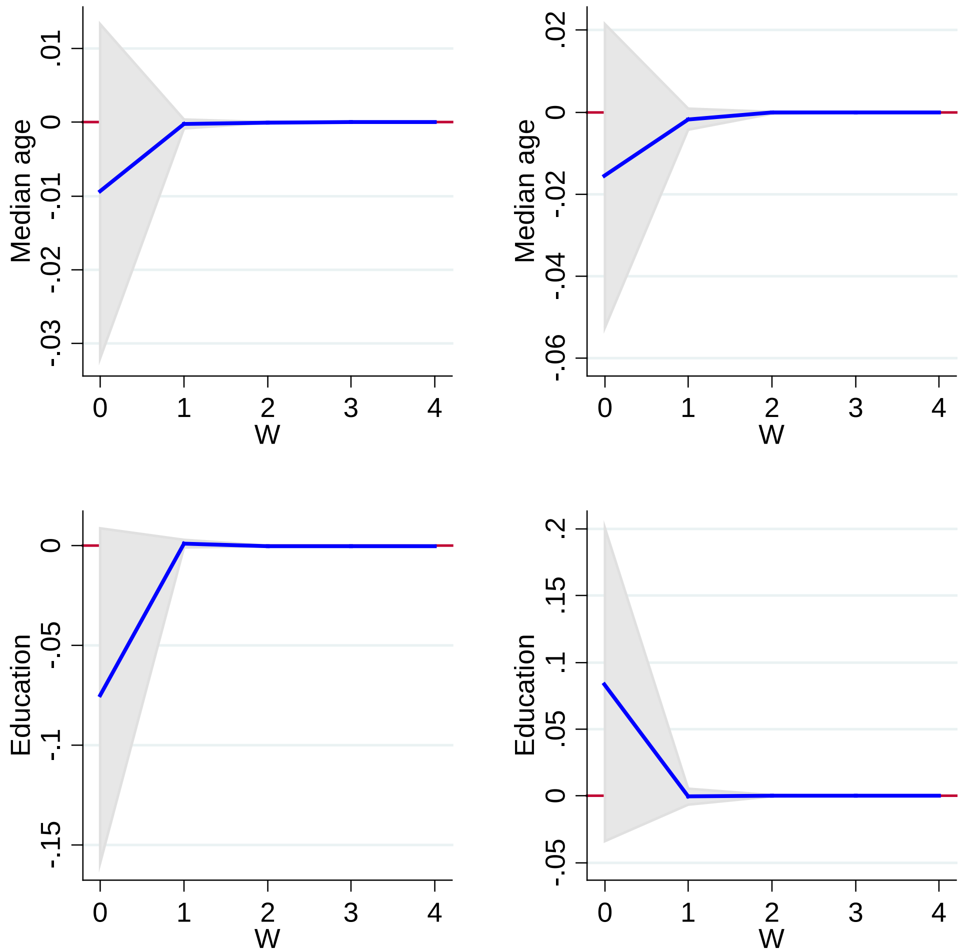


Figure A3. Direct and Indirect Effects of Income and Unemployment

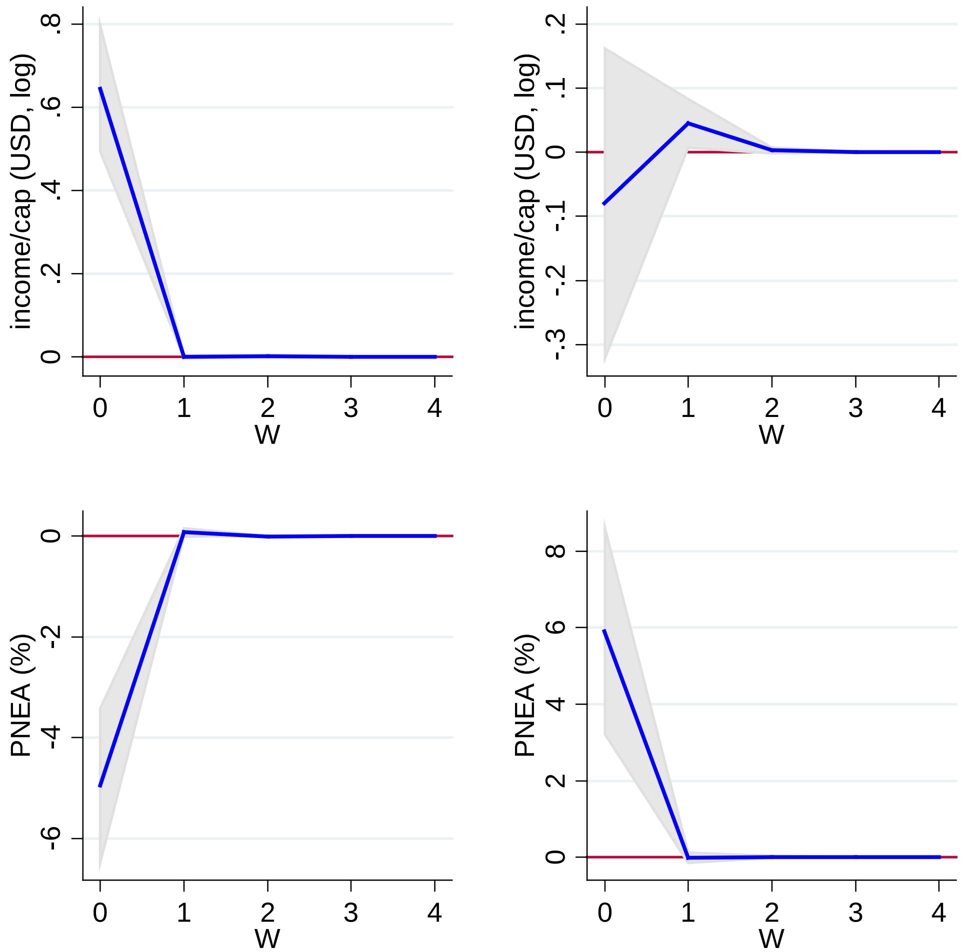


Figure A4. Direct and Indirect Effects of Inequality and Divorce Rates

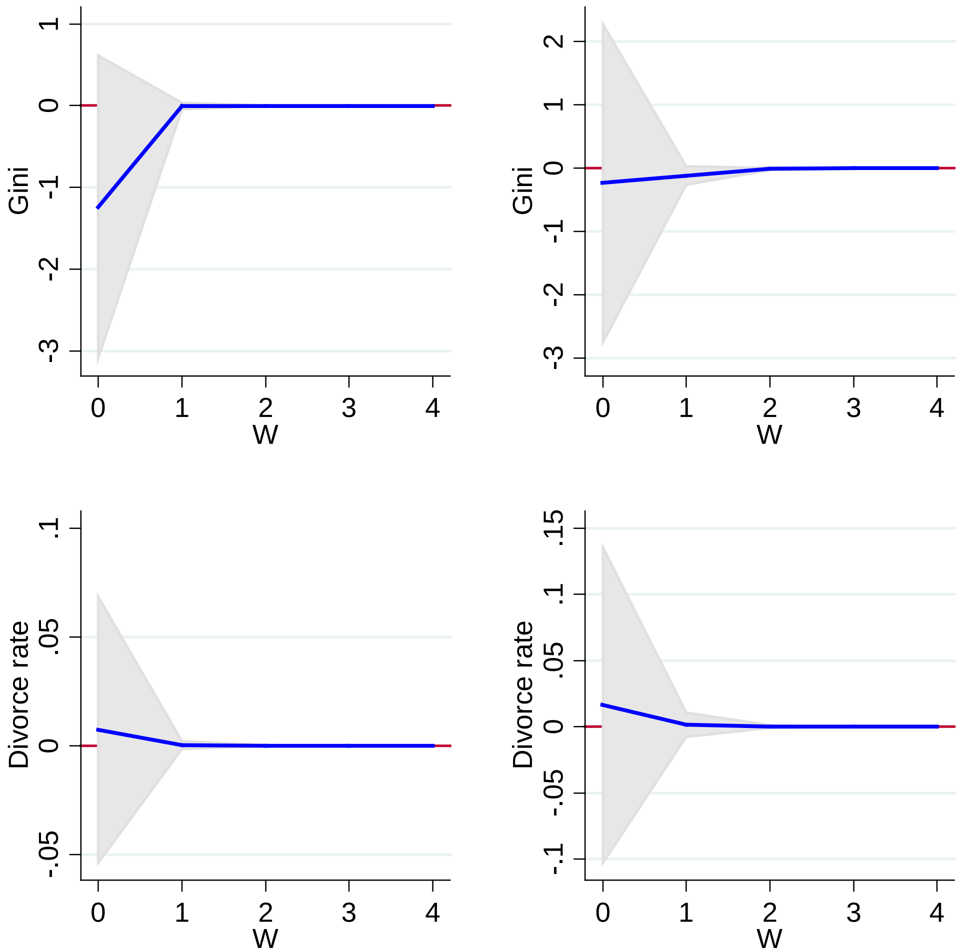


Figure A5. Direct and Indirect Effects of Turnover and Participation

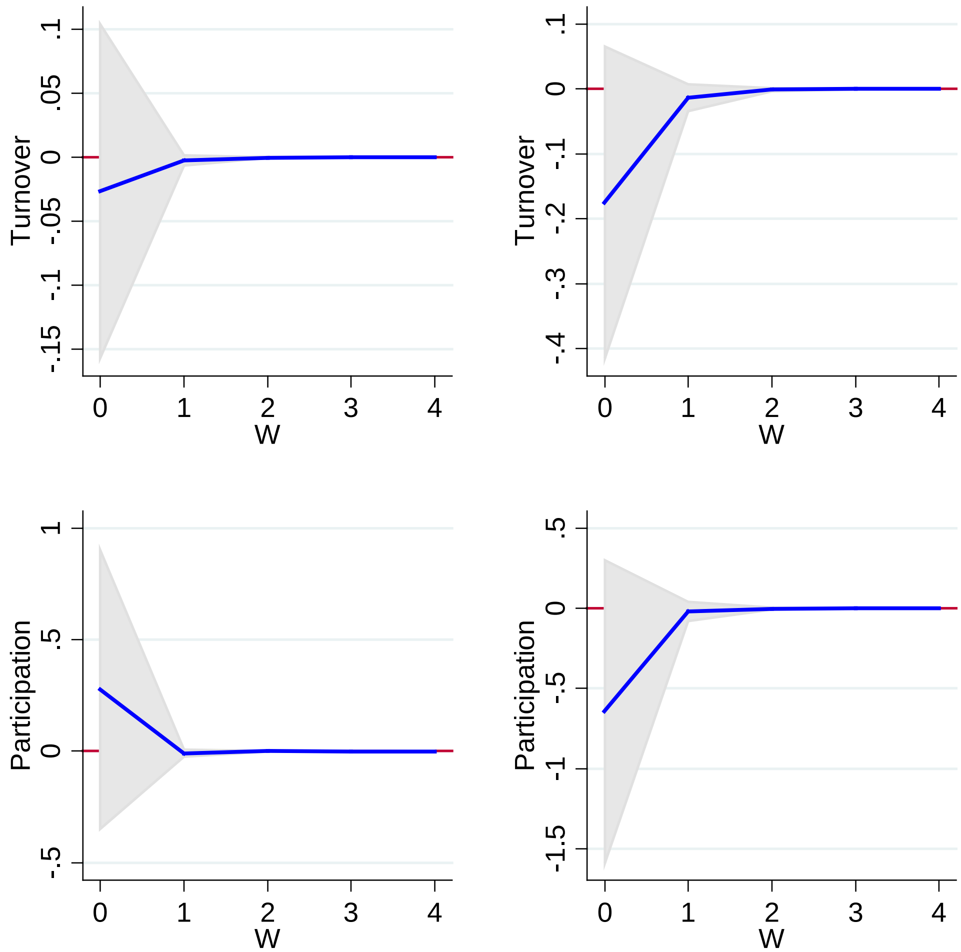


Figure A6. Direct and Indirect Effects of Uneven Terrain (altitude, s.d., logged)