



**Homicide in El Salvador’s Municipalities:  
Spatial Clusters and the Causal Role of  
Neighborhood Effects, Population Pressures, Poverty, and Education**

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*Editor’s Note: The following is a “Working Paper” by two outstanding scholars using innovative analytical tools and methodology – spatial cluster analysis – that identify important causal relationships between social factors and homicides in municipalities in El Salvador. The Wilson Center has already collaborated with one of the authors, Matthew Ingram, on two studies using similar approaches in Mexico. Given the ongoing public debate about the factors contributing to a rapid increase in child migrants from Central America, the Wilson Center felt it was important to make Ingram and Curtis’s research available in this preliminary form. A final and expanded version of this research will be available later this fall.*

**Introduction**

Violence directly affects individual and community wellbeing, and is also increasingly understood to undercut democracy and development. For public health scholars, violence presents a direct harm to health and wellbeing. In the worst cases, violence is lethal. Violence also generates serious costs to democracy. Fear and insecurity erode public trust and interpersonal confidence, hindering civic engagement and participation in public life. Further, low public trust undermines the legitimacy of democratic institutions, and persistent insecurity can generate support for heavy-handed or authoritarian policies<sup>2</sup>. Indeed, in some new democracies in the region, including El Salvador, frustration with criminal violence has led

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<sup>2</sup> Margaret Sarles, “USAID’s Support of Justice Reform in Latin America,” In *Rule of Law in Latin America: The International Promotion of Judicial Reform*, ed. Pilar Domingo, et al. (London: Institute of Latin American Studies, University of London, 2001).

majorities to support a return to authoritarian government<sup>3</sup>. Across the region, polls identify crime and citizen security as top policy priorities<sup>4</sup>. Thus, the prevention and reduction of violence is crucial to democratic stability. Lastly, violence generates heavy economic costs, dampening development. In the U.S., Miller and Cohen (1997) estimated the annual financial costs of gun shots alone at \$126 billion. Similarly, the Inter-American Development Bank (IDB) found that the health care costs of violence constituted 1.9 percent of Gross Domestic Product in Brazil, 5.0 percent in Colombia, 4.3 percent in El Salvador, 1.3 percent in Mexico, 1.5 percent in Peru and 0.3 percent in Venezuela<sup>5</sup>. Along with law enforcement costs, costs to the court system, economic losses due to violence, and the cost of private security, violent crime has been estimated to cost Brazil 10.5 percent of GDP, Venezuela 11.3 percent, Mexico 12.3 percent, and El Salvador and Colombia more than 24 percent of GDP<sup>6</sup>. Restating, violence costs several countries, including El Salvador, 10-20 percent of GDP. Given that GDP growth rates of three to four percent would be considered healthy, a substantial reduction of violence in these countries would have dramatic benefits for development. In sum, concerns about public health, democracy, and development motivate the need for a better understanding of the patterns and causes of violence, and of the need to translate this understanding into improved violence-reduction policies.

The intensity of violence in Latin America, particularly in Central America, also motivates this study. The United Nations Office on Drugs and Crime reports homicide rates for the major regions of the world for the 17 years from 1995-2011.<sup>7</sup> UNODC data reveal two patterns that set Latin America apart. First, homicide rates in this region are much higher than in other regions, and much higher than the global average. Specifically, homicide rates in Latin America have been four to six times higher than those in North America. For instance, while the U.S. homicide rate was 5 per 100,000 in 2010, the rate for Latin America was approaching 30. Figure 1 graphs these regional trends, showing the high and increasing homicide rates in Latin America and the Caribbean.

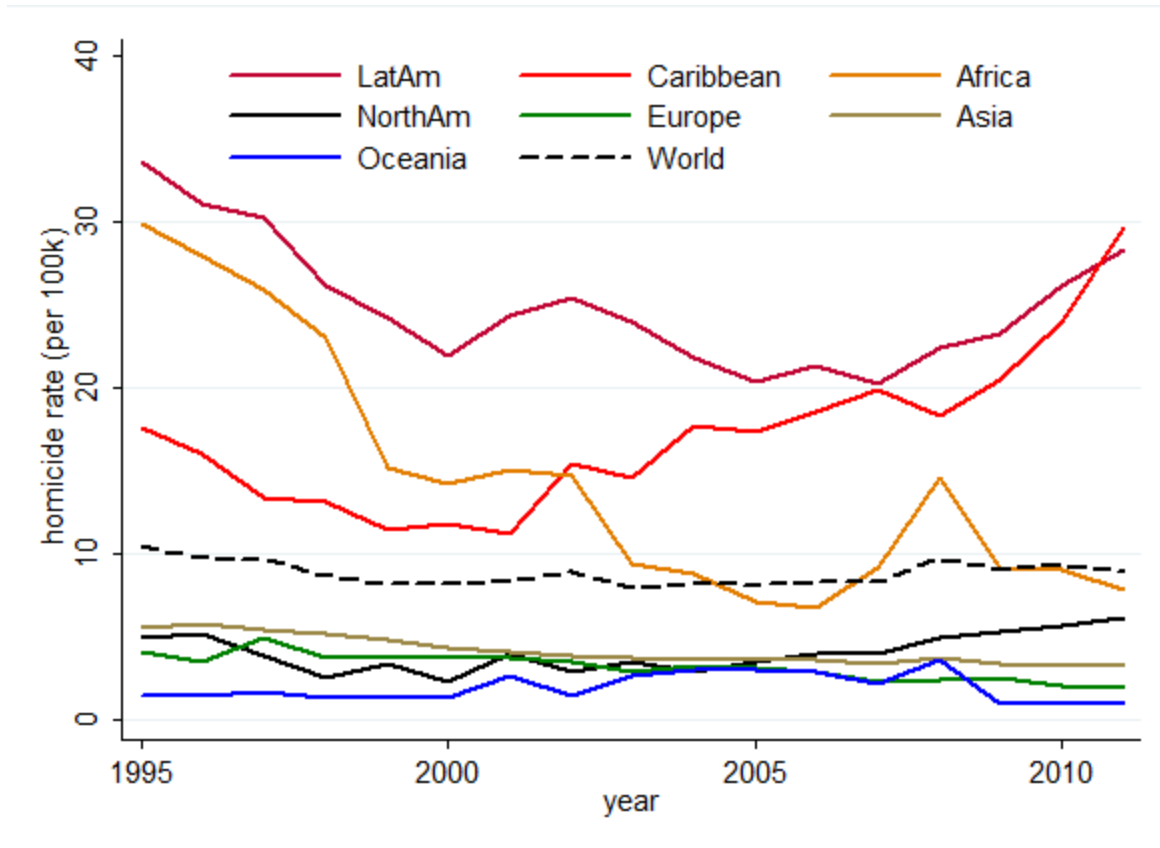
<sup>3</sup> Jose Miguel Cruz, "The Impact of Violent Crime on the Political Culture of Latin America: The Special Case of Central America," In *Challenges to Democracy in Latin America and the Caribbean: Evidence from the Americas Barometer 2006-2007*, ed. Mitchell A. Seligson (Nashville: Vanderbilt University, 2008), 241, noting similar survey results in Guatemala and Honduras.

<sup>4</sup> Marta Lagos and Lucía Dammert, "La Seguridad Ciudadana: El problema principal de América Latina," May 9, 2012, Corporación Latinobarómetro, [http://www.latinobarometro.org/documentos/LATBD\\_La\\_seguridad\\_ciudadana.pdf](http://www.latinobarometro.org/documentos/LATBD_La_seguridad_ciudadana.pdf).

<sup>5</sup> Juan Luis Londoño and Rodrigo Guerrero, "Violencia en América Latina: Epidemiología y Costos," Documento de Trabajo R-375, (Washington, D.C.: Banco Interamericano de Desarrollo, 1999); Buvinic M, Morrison A. "Violence as an obstacle to development." Washington, DC, Inter-American Development Bank, 1999:1-8 (Technical Note 4: Economic and social consequences of violence), cited in World Health Organization (2002), *World report on violence and health*, Geneva, Switzerland: 12.

<sup>6</sup> Londoño and Guerrero, "Violencia en América Latina: Epidemiología y Costos," 26.; Robert L. Ayres (1998), "Crime and violence as development issues in Latin America and the Caribbean" Washington, DC: World Bank; cited in Paulo de Mesquita Neto (2006), "Public-Private Partnerships for Police Reform in Brazil", in John Bailey and Lucia Dammert, eds., *Public Security and Police Reform in the Americas*, Pittsburgh, Pittsburgh University Press, 49.

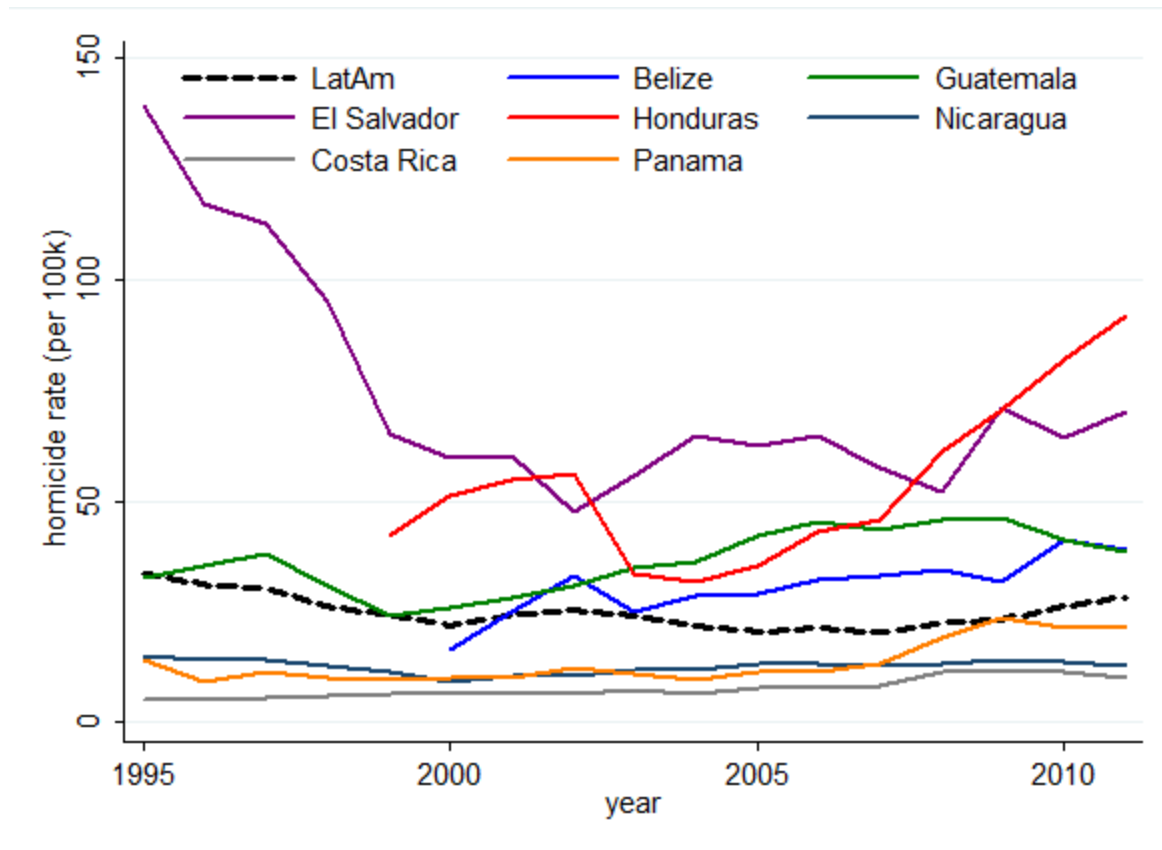
<sup>7</sup> United Nations Office on Drugs and Crime, *Global Study on Homicide 2013: Trends, Contexts, Data* (Vienna: United Nations Office on Drugs and Crime, 2014), <http://www.unodc.org/gsh/>.



**Figure 1. Homicide Rates Across World Regions, 1995-2011.**

Focusing on Central America, Figure 2 graphs homicide rates for the Central American nations from 1995-2011 in reference to the already high and increasing rate for Latin America (dotted line). Notably, El Salvador and Honduras reported the two highest homicide rates in the world for the three years from 2009-11.<sup>8</sup> Indeed, comparing the scales of the vertical y-axes from both figures reveals that homicide rates in El Salvador have been persistently above even the maximum value on the y-axis of Figure 1. National homicide rates only recently dropped below 100 in El Salvador, and while the national rate dropped below 50 in 2012, subnationally there are multiple municipalities with rates over 100, and these communities co-exist with other communities that do not experience any homicides (see below).

<sup>8</sup> United Nations Office on Drugs and Crime, *Global Study on Homicide 2013*.



**Figure 2. Homicide Rates Across Central American Countries, 1995-2011.**

This paper examines this subnational variation in homicide rates within El Salvador, aiming to identify patterns that can help improve violence-reduction policies. The paper proceeds as follows. First, Section 1 closely examines subnational patterns of variation in homicide, highlighting the benefits of a municipal-level of analysis over national or departmental perspectives that obscure substantial information at the lower, municipal level. This section visualizes data on aggregate homicides for 2012 and 2013, female victims (“femicides”) for 2013, and youth homicides for 2012, presenting these data in maps. Section 3 introduces the theoretical background for an explanatory analysis of homicide, identifying specific working hypotheses regarding social, economic, and institutional factors anticipated to have a causal relationship with homicide. Section 3 clarifies sources and methods. Section 4.1 undertakes an exploratory spatial analysis of the data mapped in Section 1, testing whether the various types of homicide are distributed in a spatially random manner across El Salvador’s 261 municipalities. Again, the benefits of a municipal level of analysis are emphasized, and the section identifies specific municipalities that constitute cores of statistically significant clusters of violence. Section 4.2 adds a brief explanatory analysis based on a spatial regression model. Looking ahead, the findings suggest that violence clusters geographically in non-random ways, violence in one municipality spills over into homicide in neighboring municipalities, population pressures

exert an expected upward pressure on homicide rates, poverty exerts an unexpected downward pressure on homicide rates, and education exerts an expected downward pressure on homicide rates. Finally, the conclusion revisits the main findings and discusses policy implications. While the population finding does not translate into clear policy program, and the poverty finding requires additional research to understand the causal process underlying the result, the other findings yield clear policy implications. Specifically, violence-reduction policies should be targeted regionally rather than at isolated communities, policies aimed at femicides and youth homicides should be targeted at different geographic regions than policies aimed at homicide more generally, and policies need to emphasize long-term investment in education.

### 1. Homicide in El Salvador: A Closer Look

This section unpacks homicide data in El Salvador in three ways. First, the analysis shifts from national-level data to departmental- and municipal-level data. Second, 2013 data are compared with 2012 data to gauge the temporal stability of patterns in the most recent, 2013 data. Finally, aggregate homicide data are disaggregated into femicides, male victims, and youth victims. Data differentiated by sex was available only for 2013, and data differentiated by age was available only for 2012. Throughout, the goal of disaggregating data in these ways is to identify strategies to improve the targeting of violence-reduction policies.

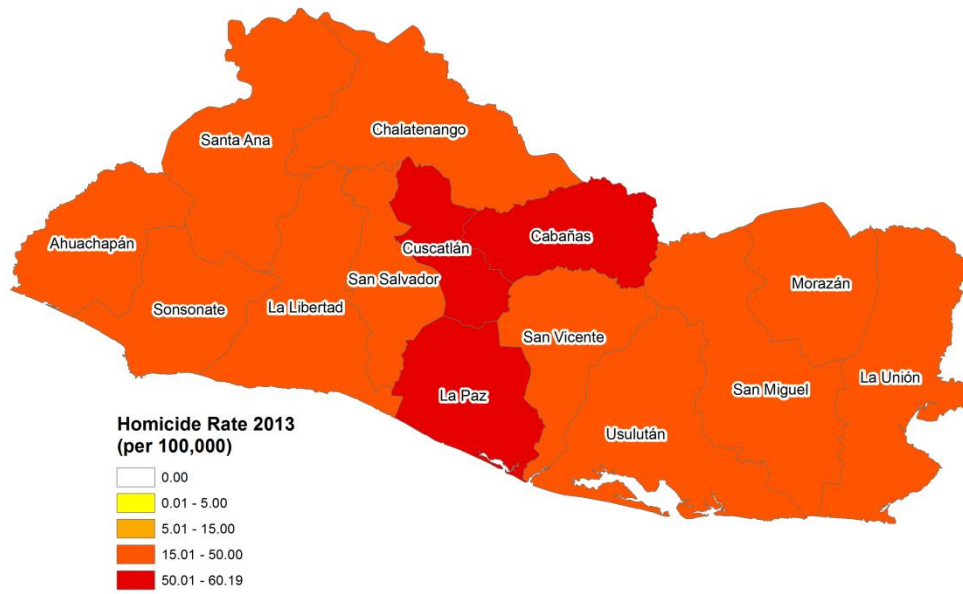
The national-level data in Figure 2 spanned 1995-2011. At the end of that time span, 2011, the national homicide rate in El Salvador stood at 70.19. The rate dropped in 2012 and 2013 to 41.91 and 40.98, respectively<sup>9</sup>. By these national figures, El Salvador still has a high rate – eight times the U.S. rate and about 30 percent higher than Mexico, where the homicide rate has tripled since 2007<sup>10</sup>– but it has dropped significantly over the last 10-15 years, especially if we consider the extraordinarily high homicide rates in the mid-1990s, soon after the end of the civil war.

However, this national level of analysis obscures meaningful variation among different administrative units within El Salvador<sup>11</sup>. Figures 3 and 4 illustrate how a department-level analysis obscures rich information at the municipal level. Figure 3 maps 2013 homicide rates (per 100,000 people) across El Salvador's 14 departments. Figure 4 then maps the same data across the country's 261 municipalities (see

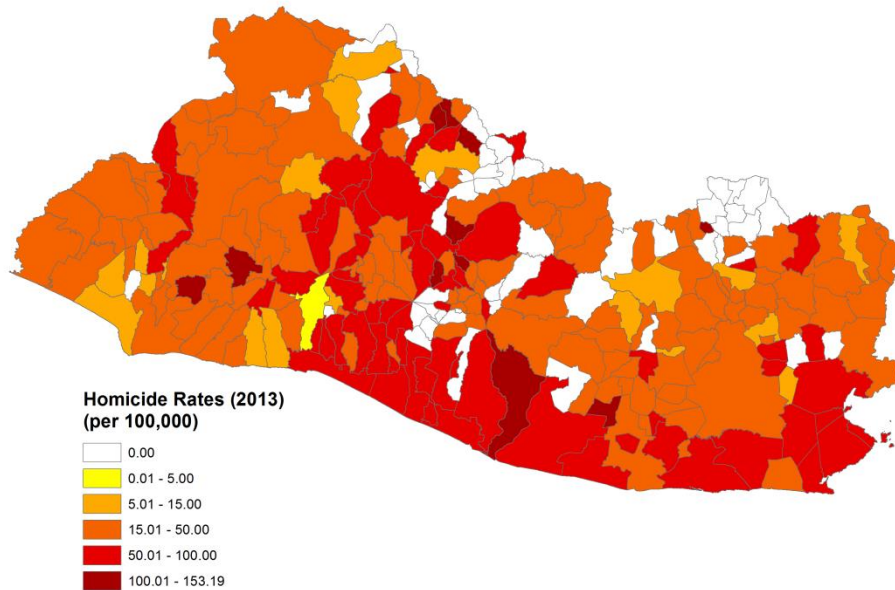
<sup>9</sup> IML 2013; using 2007 population as the denominator, which was the last census year

<sup>10</sup> Alejandro Hope. 2014. "Not quite at war, not yet at peace." Presentation at Woodrow Wilson Center, Jan. 16. Available at: <http://www.wilsoncenter.org/event/security-mexico-pena-nieto-administration-review> (viewed Mar. 11, 2014); Matthew C. Ingram, "Community Resilience to Violence: Local Schools, Regional Economies, and Homicide in Mexico's Municipalities," In *Building Resilient Communities in Mexico: Civic Responses to Crime and Violence*, ed. by David A. Shirk, et al. (Washington, DC: Woodrow Wilson Center and Justice in Mexico Project, 2014).

<sup>11</sup> See, eg, Adam Storeygard, Deborah Balk, Marc Levy, and Glenn Deane, "The global distribution of infant mortality: a subnational spatial view," *Population, Space and Place* 14 (2008).



**Figure 3. Homicide Rates (2013) at Department Level.**



**Figure 4. Homicide Rates at Municipal Level (2013).**

Data and Methods for data sources).<sup>12</sup> In these maps, darker colors identify areas with higher homicide rates and lighter colors identify areas with lower homicide rates.

The map in Figure 3 suggests that the main administrative areas with high levels of violence are the three central departments of Cabañas, Cuscatlán, and La Paz, and that otherwise violence is fairly uniform at rates between 15 and 50. Notably, Figure 3 suggests that the areas with the highest homicide rate do not exceed 60.19, and conversely that there are no violence-free areas in the country.

Figure 4, however, reveals the much wider variation at the municipal level that was obscured in Figure 3. Indeed, some municipalities exhibit homicide rates well above 100, while at the same time substantial portions of the country are free of homicides. Also, while some of the units with the highest homicide rates (dark red) appear to be in the central departments identified earlier, there are several others that are in other parts of the country. Further, even a cursory examination of this map suggests that communities bordering the Pacific coast experience high levels of violence (bright red), especially the eastern two-thirds of the coastal communities.

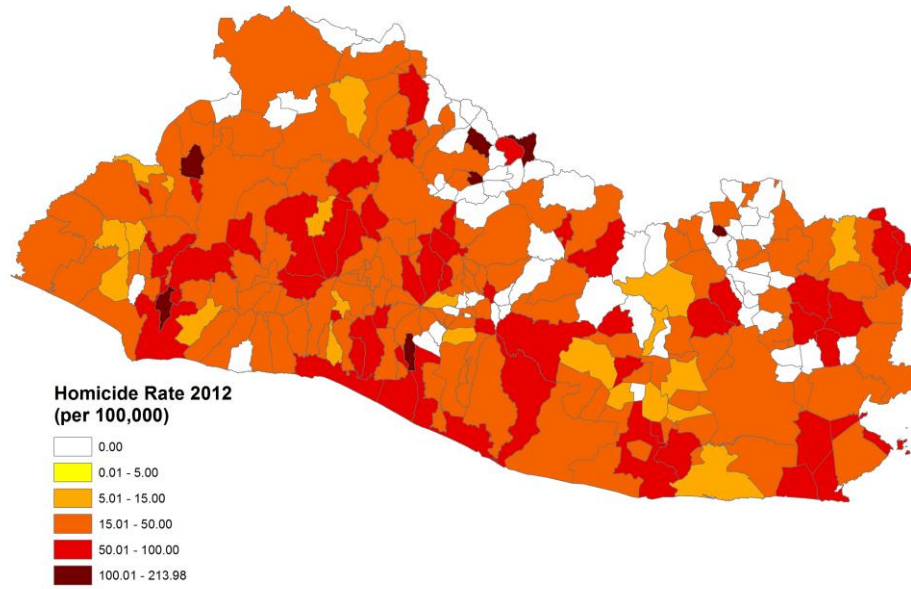
The much richer variation that is evident with a municipal level of analysis can be leveraged to target violence-reduction policies in a way that is not possible with the departmental data alone. For instance, a policy based on the department-level data might suggest that resources should be directed at the three centrally-located departments with the highest homicide rates. However, the municipal-level map shows that there are several municipalities within these departments that have no homicides, and conversely that there are several municipalities outside these departments with much worse problems of violence. Thus, a policy based on the departmental data would be inefficient in that it would direct resources where they are not needed and divert resources from where they are needed. That is, just as national-level data obscure meaningful variation and policy-relevant information among departments, department-level data obscures this variation and information among municipalities. For these reasons, the rest of this paper adopts a municipal-level perspective, aiming to identify ways to improve the targeting of violence-reduction policies.

2013 is the most recent year for which data are available, but a comparison of data from 2012 and 2013 allows an assessment of the stability of the patterns observed in 2013. Figure 5 maps 2012 homicide rates, and Figure 6 maps the average homicide rate from 2012-13.

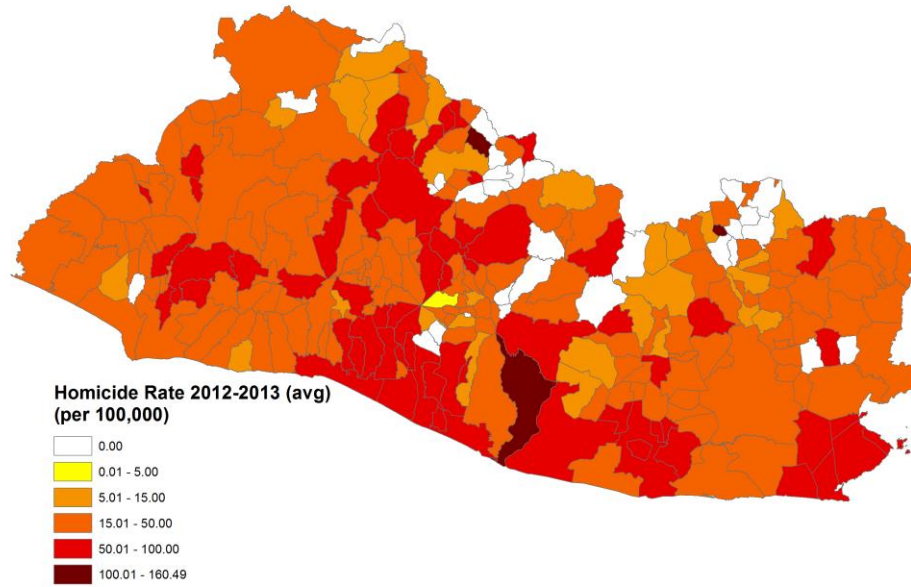
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<sup>12</sup> El Salvador generally reports 262 municipalities. However, one of these municipalities, Meanguera del Golfo, is an island in the Gulf of Fonseca near the border with Honduras and Nicaragua, and little data is available for this unit. Thus, it is excluded from the analysis. See Data and Methods.





**Figure 5. Homicide Rates (2012).**

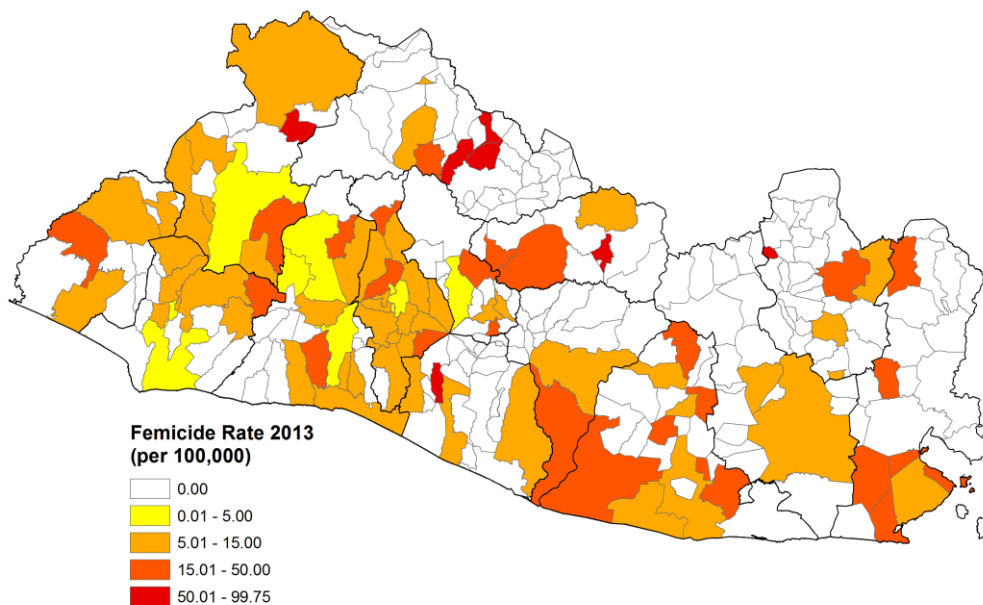


**Figure 6. Homicide Rates, Average for 2012-2013.**

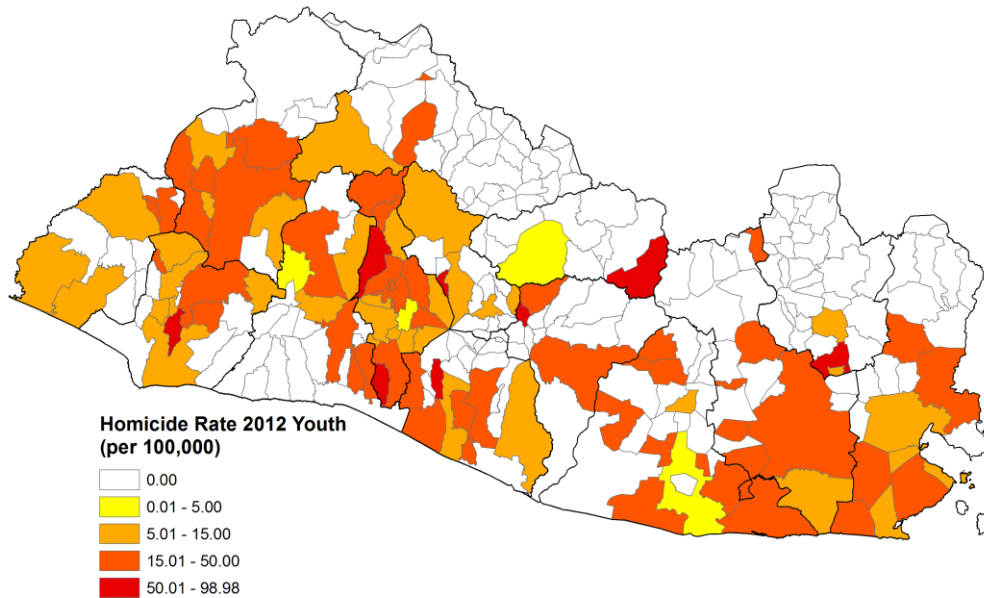


In both 2012 and 2013, there is wide variation in homicide rates across municipalities. In 2012, however, the range for these rates was much larger, as there were still some municipalities with no homicides but the rate peaked at over 200, well above the highest rate in 2013. Turning to the average rate for 2012-13, Figure 6 shows the overall pattern from 2013 remains even after averaging with the 2012 data. Thus, homicide rates overall appear to have decreased from 2012 to 2013, continuing the national trend noted earlier. Further, according to the most recent data available, the overall pattern of wide variation and some concentration of violence along coastal communities appears stable across the most recent single-year measure (2013) and the most recent two-year measure (2012-13).

Beyond variation over time, available data also allow an examination of homicides of women (i.e., femicide) and homicides of youths (ages 0-17). Figure 7 reports femicide rates and Figure 8 reports homicides of youths. The patterns for femicides and youths are quite different from the overall pattern, offering additional evidence to inform the targeting of violence-prevention policies for these particular kinds of homicides. At first glance, femicide appears to be concentrated in smaller pockets of the country, primarily in the northern department of Chalatenango, along the border with Honduras. Youth homicides appear to be more heavily concentrated around the nation's capital – in and around the department of San Salvador – and also in the southeastern part of the country, near the Gulf of Fonseca.



**Figure 7. Femicide Rate (2013).**



**Figure 8. Youth Homicide Rate (2012).**

The remainder of this paper undertakes a spatial analysis of the data presented thus far, including exploratory analyses of spatial clusters and a spatial regression model of the aggregate homicide measure for 2013. First, we outline a theoretical expectations that motivation the explanatory analysis and then describe our data and methods.

## **2. Explaining Violence: Theoretical Framework and Working Hypotheses**

Sociologists and criminologists have found an association between a large array of structural features of communities – macro-level and slow-moving demographic, economic, and social conditions – and the rate of crime in those communities. While these pressures help understand root causes of violence and therefore can guide governments’ proactive policy responses in each of these areas in order to prevent criminality in the first place, governments can also influence violence via more reactive public safety efforts once patterns of criminality emerge, primarily via investment in the size and quality of its public safety and security forces, or state capacity. We draw on these theories to help to explain variation in homicide rates across El Salvador’s municipalities.

**Social Disorganization.** Research in sociology and criminology on the role of community context<sup>13</sup>, “collective efficacy”<sup>14</sup>, and social context<sup>15</sup> in explaining crime and violence provide a central theoretical framework for explaining variation in homicide rates. According to Sampson and Groves—and following earlier research by Shaw and McKay (1942; 1969)—violence is a consequence, in part, of social disorganization, and social disorganization can be measured by its external sources, including resource deprivation or socioeconomic status (SES), residential mobility, and ethnic heterogeneity. With regards to the presence or absence of material resources, Pridemore (2011), in his review of the cross-national literature, found that higher rates of poverty have consistently been linked to higher rates of homicide in the U.S. and abroad. Other contributing factors include family disruption, which “may decrease informal social control at the community level”<sup>16</sup>, and urbanization, which “weaken[s] local kinship and friendship networks and impede[s] social participation”<sup>17</sup>. Thus, for Sampson and Groves, community capacity to remain organized, i.e., to resist disorganization and therefore reduce crime, is shaped by macro-social and macro-economic factors like resource deprivation, residential instability, ethnic heterogeneity, family disruption, and urbanization.<sup>18</sup>

Complementing the above discussion, Bursik and Grasmick<sup>19</sup> theorized that the more disorganized a community (here: municipality) is, the more crime – both violent and acquisitive – will occur as a response to and product of the social disorganization. Communities can become more disorganized as demographic pressures shift, either through population growth, population concentration, mobility or migration, the breakdown of family structures, and increased ethnic heterogeneity. Bursik and Grasmick<sup>20</sup> discovered that ethnically diverse communities experience tension between different ethnic groups for many reasons. Ethnic groups typically have different primary languages, practices, and networks from one another and from the majority group in the area, which can hinder the organization of the entire community. Additionally, any tension present between ethnic groups may lead to violence (especially that of racially based gangs).

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<sup>13</sup> Robert J. Sampson and W. Byron Groves, "Community Structure And Crime: Testing Social-Disorganization Theory." *American Journal of Sociology* 94 (1989).; Robert Bursik and Harold G. Grasmick, *Neighborhoods and crime: the dimensions of effective community control* (New York: Lexington Books, 1993).

<sup>14</sup> R. J. Sampson, "Neighborhoods and Violent Crime: A Multilevel Study of Collective Efficacy," *Science* 277 (1997).

<sup>15</sup> Sara K. Thompson and Rosemary Gartner . "The Spatial Distribution and Social Context of Homicide in Toronto's Neighborhoods," *Journal of Research in Crime and Delinquency* 51 (2014).

<sup>16</sup> Robert J. Sampson and W. Byron Groves, "Community Structure And Crime: Testing Social-Disorganization Theory." *American Journal of Sociology* 94 (1989) 781; citing Sampson, Robert J.. "Effects of Socioeconomic Context on Official Reaction to Juvenile Delinquency." *American Sociological Review* 51, no. 6 (1986): 876-85)  
<sup>17</sup> (782)

<sup>18</sup> According to these authors, these structural factors are also mediated by informal social features of communities, including the ability to supervise teenage groups, the size and density of friendship networks, and participation or engagement in civic life.

<sup>19</sup> Bursik and Grasmick, *Neighborhoods and crime: the dimensions of effective community control*.

<sup>20</sup> Ibid.

Along similar lines, Land et al.<sup>21</sup> established three principal components from the primary predictors of interest.<sup>22</sup> These three composite measures captured (1) population pressures, (2) resource deprivation/affluence, and (3) family disruption<sup>23</sup>). Population pressures include total population and population density or concentration, but can also extend to other demographic pressures like age structure and, since most crime is committed by young males, the proportion of the population that is young and male. Indicators of resource deprivation or affluence include income, inequality, and poverty rates. Lastly, family disruption has been measured using divorce rates<sup>24</sup>, but could also be captured by indicators of single-parent households, especially those headed by women.

In short, all else being equal, we anticipate that population pressures, urbanization, family structure, and ethnic heterogeneity contribute to social disorganization. Thus, key indicators of social disorganization include population growth, population density, degree of urbanization, percentage of households headed by single women, and percentage of the population that is indigenous. Further, we anticipate that each of these indicators will have a positive relationship with homicide rates. To be sure, urban centers may be home to many risk factors for violence, but urban areas can also be sources of factors that are protective against violence, including increased law enforcement presence<sup>25</sup>. We return to the issue of law enforcement presence below, but for now anticipate that the indicators of social disorganization identified above will have a positive relationship with violence, while we also remain cognizant that some of these indicators may be capturing some of the protective effects associated with urban areas.

**Education.** Education is widely regarded as having a protective effect against violence<sup>26</sup>, especial against homicide<sup>27</sup>. Education exerts this protective effect in both direct and indirect ways. Directly, as more individuals, especially young men, are in school, they are not elsewhere, e.g., spending time on the street, so they are less likely to be either victim or perpetrator. That is, higher levels of educational enrollment and attainment suggest that children stay in school longer

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<sup>21</sup> Kenneth Land, Patricia L. McCall, and Lawrence E. Cohen, "Structural Covariates Of Homicide Rates: Are There Any Invariances Across Time And Social Space?," *American Journal of Sociology* 95 (1990).

<sup>22</sup> However, in large-N regression analyses seeking to explain variation in crime rates, inconsistent results were common (Baller et al. 2001, 562); that much of this inconsistency was due to multicollinearity among the explanatory variables, and generated

<sup>23</sup> (see also Robert D. Baller, Luc Anselin, Steven F. Messner, Glenn Deane, and Darnell F. Hawkins, "Structural Covariates Of U.S. County Homicide Rates: Incorporating Spatial Effects." *Criminology* 39 (2001): 562, 568.

<sup>24</sup> Land, McCall and Cohen, "Structural Covariates Of Homicide Rates: Are There Any Invariances Across Time And Social Space?," 922.; Baller, Anselin, Messner, Deane, and Hawkins, "Structural Covariates Of U.S. County Homicide Rates: Incorporating Spatial Effects," 561-588.

<sup>25</sup> United Nations Office on Drugs and Crime, *Global Study on Homicide 2013*, 7.

<sup>26</sup> Gottfredson, Denise C. "Youth employment, crime, and schooling: A longitudinal study of a national sample." *Developmental Psychology* 21, no. 3 (1985): 419-432; Farrington, David, Bernard Gallagher, Lynda Morley, Raymond St. Ledger, and Donald West. "Unemployment, School Leaving and Crime." *British Journal of Criminology* 26, no. 4 (1986): 335-356; Ruhm, Christopher J.. "Are Recessions Good For Your Health?." *Quarterly Journal of Economics* 115, no. 2 (2000): 617-650, at 624)

<sup>27</sup> Lance Lochner and Enrico Moretti, "The Effect of Education on Crime: Evidence from Prison Inmates, Arrests, and Self-Reports," *American Economic Review* 94 (2004) 175-177.

and in a safe, productive, socially controlled environment away from crime. Thus, school enrollment rates, attendance rates, time spent in school, and other measures of educational attainment should have a negative relationship with violence. Indirect effects play out over longer term. A population that is more educated is generally able to obtain better employment, stay employed, and both maximize available opportunities and overcome adversity. Thus, a better educated population is more likely to find rewarding activity in the legal, formal economy. Further, if opportunities for crime arise, a better educated individual is more likely and better able to assess the material costs of engaging in criminal behavior, including the potential costs of losing one's job or being incarcerated. Since violent crime, especially homicide, incurs high costs of this type, education should be a particularly important protective barrier to engaging in violent crime. Additionally, since past criminal activity is a predictor of future criminal activity, individuals who have spent more time in school – and therefore away from crime – are less likely to engage in future crime, and potentially have a cultural, ideational, ethical aversion to crime that is more reinforced than in people who did not spend time in school and perhaps engaged in other, even petty types of crime at an earlier age. Lastly, education allows citizens to communicate more effectively with each other, learn each other's language, and strengthen community ties to improve the social interactions. In many ways, education can help counter the negative effects of social disorganization outlined previously. Literacy rates and other measures of educational attainment, therefore, should have a negative relationship with violence.

***Economic Activity.*** Beyond the structural conditions of income, inequality, and poverty rates discussed earlier, the level of economic activity in a community can have an effect on crime and violence. The general expectation is that weak economies or economic downturns push people out of work or out of full employment, and this unemployment or under-employment creates financial stress and therefore generate incentives illegal activity. Citizens may become frustrated by the lack of economic opportunities and seek illegitimate means to overcome this economic strain. One route may be to turn to acquisitive crimes and black markets for income. The risk of violence increases during the commission of property crimes (e.g., a burglar may encounter an occupant in a home), and interactions with black markets also raise the risk of violence, given that participants cannot rely on lawful measures (i.e., police) when wronged by others in these settings. Thus, Rosenfeld<sup>28</sup> argues the anomic strain created by unemployment and a poorer economic system, along with poverty, increases homicide indirectly through property crime

In the U.S., existing research finds a firm relationship between economic downturns and an increase in property crime, but the relationship appears to reverse for economic downturns and homicide<sup>29</sup>. This counterintuitive relationship has also been found in Mexico<sup>30</sup>. An

<sup>28</sup> Richard Rosenfeld, "Crime Is The Problem: Homicide, Acquisitive Crime, And Economic Conditions," *Journal of Quantitative Criminology* 25 (2009).

<sup>29</sup> Steven Raphael and Rudolf Winter-Ebmer, "Identifying The Effect Of Unemployment On Crime," *The Journal of Law and Economics* 44 (2001) 271-277.

<sup>30</sup> Ingram, "Community Resilience to Violence: Local Schools, Regional Economies, and Homicide in Mexico's Municipalities."

alternative expectation, therefore, is that economic downturns reduce the circulation of goods and people, reducing interactions among people, and therefore decreasing opportunities for crime and violence<sup>31</sup>.

**State Capacity.** Drawing on both the armed conflict literature and research in criminology, state capacity is expected to have a negative effect on homicide rates. Weak states are those that lack the institutional capacity to support and maintain control over its citizenry effectively.<sup>32</sup> Weak governments typically have higher rates of violence (be it political or criminal) for multiple reasons, including those mentioned earlier (i.e. social disorganization, institutional anomie, etc.), but also because they are unable to respond to waves of crime when these occur. Weak states either have fewer police and security forces or forces that are more loyal to the government in charge than the well-being of local citizens. A community with fewer police per capita does not have as much external pressure to conform to the laws of society and may have more crime as a result.<sup>33</sup> We define state capacity here specifically as security capacity, or the available public safety infrastructure, and anticipate that communities with weak security infrastructure will have higher homicide rates than communities with strong security infrastructure.

### 3. Data and Methods

Violence is the outcome of interest and we measure this outcome with five variables: (1) aggregate homicide rates for 2013; (2) average homicide rates for 2012-13; (3) homicides in 2013, men only; (4) homicide rate in 2013, women only (femicides); and (5) homicides in 2012, youth only. All data are from El Salvador's Institute of Forensic Medicine, or *Instituto de Medicina Legal* (IML)<sup>34</sup>. Data reporting is uneven reporting over time. The 2012 data was reported by municipality, but only disaggregated youth homicides, not the sex of the victim. 2013 data reports homicides by municipality, but this time ignores youth homicides, and breaks down sex of victim. Taken together, the two years yield measures of overall homicide rate in 2012 and 2013, femicide rate in 2013, and youth homicide rate 2012.<sup>35</sup>

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<sup>31</sup> Raphael and Winter-Ebmer, "Identifying The Effect Of Unemployment On Crime," 276-277.

<sup>32</sup> Stewart Patrick, *Weak links: fragile states, global threats, and international security* (Oxford: Oxford University Press, 2011).

<sup>33</sup> Steven D. Levitt, "Understanding Why Crime Fell In The 1990s: Four Factors That Explain The Decline And Six That Do Not." *Journal of Economic Perspectives* 18 (2004).

<sup>34</sup> Instituto de Medicina Legal (IML). 2014. "HOMICIDIOS CONSOLIDADO AÑO 2013 SEGÚN BASE DE DATOS DEL INSTITUTO DE MEDICINA LEGAL, COTEJADA Y CONSENSUADA CON LA F.G.R. Y LA P.N.C." Available at: <http://www.transparencia.oj.gob.sv/portal/transparencia.php?opcion=13> (last accessed July 2, 2014); Instituto de Medicina Legal (IML). 2013. "HOMICIDIOS DEL AÑO 2012 TOTAL PAIS SEGÚN RECONOCIMIENTOS DE MEDICOS FORENSES Y BASE CONSENSADA ENTRE FGR, IML Y PNC." Available at: <http://www.transparencia.oj.gob.sv/portal/transparencia.php?opcion=13> (last accessed July 2, 2014).

<sup>35</sup> Several duplicate municipalities appeared in the data. We deleted the duplicates, and in all cases kept the data for the municipality with the highest number of homicides in order to avoid underreporting. Duplicate municipalities

To be sure, homicide rates provide an admittedly imperfect measure of violence in societies. However, more complete, comparative data on different types of violence are not available, so homicide rates have several methodological strengths, providing a metric that is generally available over time and across several subnational levels of government (e.g., departments and municipalities). Existing research also finds that other types of crimes track homicide rates.<sup>36</sup>

Independent variables include population size (logged), population density (population divided by the area of the municipality in square kilometers; logged), median age, percentage of the population that is male and between the ages of 15 and 30, percent of the population that is indigenous (logged), percent of the population that is rural (logged), percent of households headed by single women, per capita income (logged), general and extreme poverty rates, four measures of education level (adult literacy rate, adult illiteracy rate, percent of children ages 7-14 attending school, and percent of school-age children who were matriculated/enrolled in school), unemployment rate (logged), percent of the population age 15 and up that is economically active, and measures of police personnel and expenditures.

With the exception of data on population, poverty, and police, all independent variables are taken from the last official census in 2007 from El Salvador's national statistics office, *Dirección General de Estadística y Censos* (DIGESTYC), and are measured at the municipal level. Population figures are from 2010. Poverty rates were obtained in DIGESTYC's series of nationally-representative household surveys in 2004 (Las Encuestas de Hogares de Propósitos Múltiples; EPHM), which were the most recent. Data on police personnel and expenditures were obtained from the National Civil Police<sup>37</sup> and covered the years 2004-08. Following the armed conflict literature on state capacity, where military quality is measured as military expenditures divided by military personnel<sup>38</sup>, we measured police quality as police expenditures divided by the number of police personnel, and complemented this with a measure of expenditures per capita. Thus, using this data, we generated five individual measures of state security capacity: (1) average number of police officers per capita (logged), (2) average police expenditures per police

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included San Bartolome Perula (duplicate reported 1 homicide; kept the one reporting 4); San Francisco Menend. (2; kept one with 10); San Sebastian Salitr. (1; kept one with 11); and Santa Tecla (4; kept Nueva San Salvador, with 13).

<sup>36</sup> Scott Mainwaring, Timothy Scully, and Jorge Vargas Cullell (2010), "Measuring Success in Democratic Governance," In Mainwaring and Scully, eds., *Democratic Governance in Latin America*, Stanford, CA, Stanford University Press, at 31; John Bailey and Lucía Dammert, "Public Security and Police Reform in the Americas," In *Public security and police reform in the Americas*, (Pittsburgh: University of Pittsburgh Press, 2006), 7.

<sup>37</sup> W. F. D Gallegos, D. A. D. Machado, A. J. G. Martínez, and Manguía, E. G. A, *Territorialización de las expresiones de violencia y del gasto público destinado a seguridad ciudadana: Policía Nacional Civil 2006-2008*. (2009). [http://www.uca.edu.sv/deptos/economia/media/archivo/849b10\\_territorializaciondelasexpresionesdeviolenciaydelgasto.pdf](http://www.uca.edu.sv/deptos/economia/media/archivo/849b10_territorializaciondelasexpresionesdeviolenciaydelgasto.pdf).

<sup>38</sup> D. Scott Bennett and Allan C. Stam, "The Duration of Interstate Wars, 1816-1985," *The American Political Science Review* 90 (1996).



officer (logged), (3) average police expenditures per capita (logged), (4) expenditures per police officer in the most recent year, 2008 (untransformed), and (5) expenditures per capita in 2008 (logged).<sup>39</sup> Lastly, we generated two composite measures from available data – one for education and one for security capacity. For education, the principal component was based on all four measures (eigenvalue = 3.29, explaining 82 percent of the variation of all four individual measures; one of the individual measures (percent attendance) loaded above 82 percent, and the rest of the individual measures had factor loadings above 92 percent). For security capacity, the principal component was based on all five measures of police personnel and expenditures (eigenvalue = 4.17, with 83 percent of variation explained; all variables had factor loadings above 0.88)

Two shapefiles for El Salvador facilitate the analysis and mapping of data. Both were obtained from the national registry center, *Centro Nacional de Registros*.<sup>40</sup> The municipal shapefile used the Lambert NAD 27 projection, and the departmental shapefile used the WGS 1984 projection. The Lambert shapefile had no unidentified border zones (“zonas limitrofes”), but these zones were present in the WGS file. Thus, maps with both municipal and departmental units do not coincide exactly, though the unmatched areas have not data and are generally along the border with Honduras. Further, the Lambert shapefile contained 261 municipal units, while some data sets reported 262 units. The unit missing from the shapefile is Meanguera del Golfo (code 1410), an island in the Gulf of Fonseca off the southeastern coast of El Salvador, bordering Nicaragua and Honduras. Since there was also only sparse data for this unit, it was deleted and omitted from the analysis.

### ***Spatial Methods***

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”.<sup>41</sup> 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.”<sup>42</sup>

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<sup>39</sup>Nearly 34 municipalities had an average of \$0 expenditures budgeted to them and 0 officers assigned to them between 2004-2008. As such, the average expenditures per capita and per police officer, as well as police officers per capita, were also highly skewed from this occurrence. Therefore, logging these variables was necessary to avoid biasing the analyses. Additionally, 38 municipalities had \$0 expenditures budgeted to them from the National Civil Police, so the variables using these values required logging to prevent skew bias.

<sup>40</sup> Available at <http://www.cnr.gob.sv> (last accessed July 7, 2014).

<sup>41</sup> Baller, Anselin, Messner, Deane, and Hawkins, "Structural Covariates Of U.S. County Homicide Rates: Incorporating Spatial Effects," 563.

<sup>42</sup> Michael Don Ward and Kristian Skrede Glenditch, *Spatial regression models* (Thousand Oaks: Sage Publications, 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.<sup>43</sup> 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.

Drawing 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).<sup>44</sup> 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. LISA values can also be mapped in a LISA cluster map. According to Anselin<sup>45</sup>, this kind of map is "[a]rguably the most useful graph" in spatial analysis.

Building on the exploratory spatial techniques outlined above, fuller explanatory techniques include spatial regression models. While a full explanatory analysis is beyond the scope of this paper, we report a single spatial lag regression here, examining whether homicide rate in a municipality are influenced by homicide rates in surrounding municipalities.

Formally, the general spatial model can be expressed in matrix notation as follows<sup>46</sup>:

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

$$\varepsilon = \lambda W \varepsilon + \mu \tag{1}$$

<sup>43</sup> P. A. P. Moran, "The interpretation of statistical maps," *Journal of the Royal Statistical Society* 10 (1948); P. A. P. Moran, "A test for the serial independence of residuals," *Biometrika* 37 (1950); P. A. P. Moran, "Notes On Continuous Stochastic Phenomena," *Biometrika* 37 (1950); A. D. Cliff and J.K. Ord, *Spatial processes: models & applications* (London: Pion, 1981).

<sup>44</sup> Luc Anselin, "Local Indicators Of Spatial Association-LISA," *Geographical Analysis* 27 (1995).

<sup>45</sup> Anselin, Luc. 2005. "Exploring Spatial Data with GeoDa: A Workbook." (p140) GeoDa Center for Geospatial Analysis and Computation, Arizona State University. Accessed April 2, 2013. <https://geodacenter.asu.edu/system/files/geodaworkbook.pdf>.

<sup>46</sup> Luc Anselin, "Lagrange Multiplier Test Diagnostics for Spatial Dependence and Spatial Heterogeneity." *Geographical Analysis* 20 (1988).

In equation 1,  $\beta$  is a  $K \times 1$  vector of parameters associated with exogenous (i.e., non-lagged) variables  $X$ , which is an  $N \times K$  matrix;  $\rho$  (rho) is the coefficient for the spatially lagged dependent variable;  $\lambda$  (lambda) is the coefficient for the spatially lagged autoregressive structure of the disturbance  $\varepsilon$ , where  $\mu$  is normally distributed around zero.  $W$  is an  $N \times N$  row-standardized spatial weight matrix.

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

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

Where there is an autoregressive process in the error term but no autoregressive process in the dependent variable, i.e.,  $\rho=0$ , 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.,  $\lambda=0$ , the model reduces to the spatial lag model. Lagrange multiplier tests guide the decision-making process of selecting between OLS, spatial error, or spatial lag models. We return to a discussion of these tests below in the presentation of the spatial lag model.

Notably, spatial techniques are sensitive to the conceptualization and operationalization of spatial relationships. Here, we conceptualize municipalities as being neighbors if they share any portion of their municipal borders. Consequently, all spatial analyses were carried out using a spatial weights matrix built from a first-order queen contiguity notion of adjacency.

#### 4.1. Results 1: Exploratory Spatial Analysis

Table 1 reports global Moran's  $I$  values for each of the five measures of homicide rates. The table also reports significance values. The statistical significance allows us to confidently reject the null hypothesis of spatial randomness in the data with regards to all of the measures of homicide with the exception of femicides.

<b>Table 1. Global spatial autocorrelation (Moran's <math>I</math>)</b>		
<b>Measure</b>	<b>Moran's <math>I</math></b>	<b>p</b>
Homicides 2012	0.19	0.000
Homicides 2013	0.20	0.000
Homicides 2013 (men only)	0.19	0.000
Homicides 2013 (women only)	0.03	0.437
Homicides 2012 (youth only)	0.09	0.001

Beyond these indications of global spatial clustering, Figures 9-17 report LISA cluster maps showing the distribution of statistically significant clusters (see Data and Methods for discussion of local indicators of spatial autocorrelation). White areas are regions of spatial randomness in the distribution of violence, while colored areas are units that form the core of non-random spatial clusters. All cluster associations are significant at least at the .05 level. 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 ones, and the true size of the spatial cluster is larger than the colored cores.<sup>47</sup>

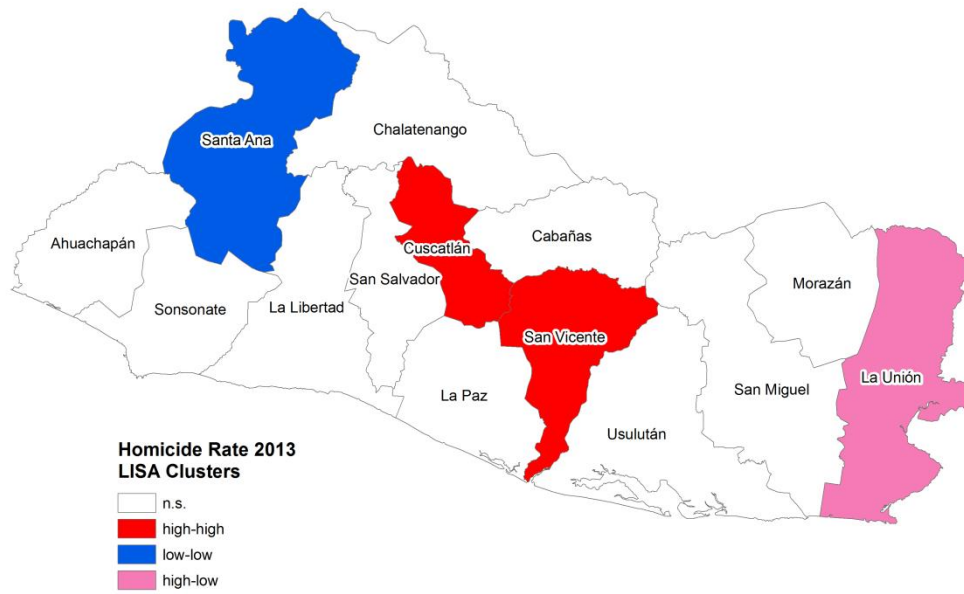
The LISA cluster map also identifies the substantive content of those clusters. Red identifies those municipalities with high levels of homicide that are surrounded by municipalities with similarly high levels of homicide (high-high). Blue identifies units with low homicide levels surrounded by units 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).

Figure 9 begins with a departmental view of LISA clusters for the aggregate 2013 data. At this level of analysis, the evidence suggests that there is a large cluster of high violence centered around the departments of Cuscatlán and San Vicente, and a cluster of low violence in the northwest, around the department of Santa Ana. As was the case with the choropleth maps in Figures 1-8, however, this department-level perspective obscures rich information at the municipal level of analysis, starting with Figure 10. Figure 10 shows that, unlike the concentration of violence in the center of the country as suggested by Figure 9, there are clusters of violence in the central region, but more extended clusters along the coast, especially the eastern two-third of the coast. Also, there are multiple areas within departments that are not experiencing high levels of violence even though there may be municipal clusters of violence within the same department. Thus, the municipal level LISA clusters provide valuable information for targeting policies to prevent or respond to violence.

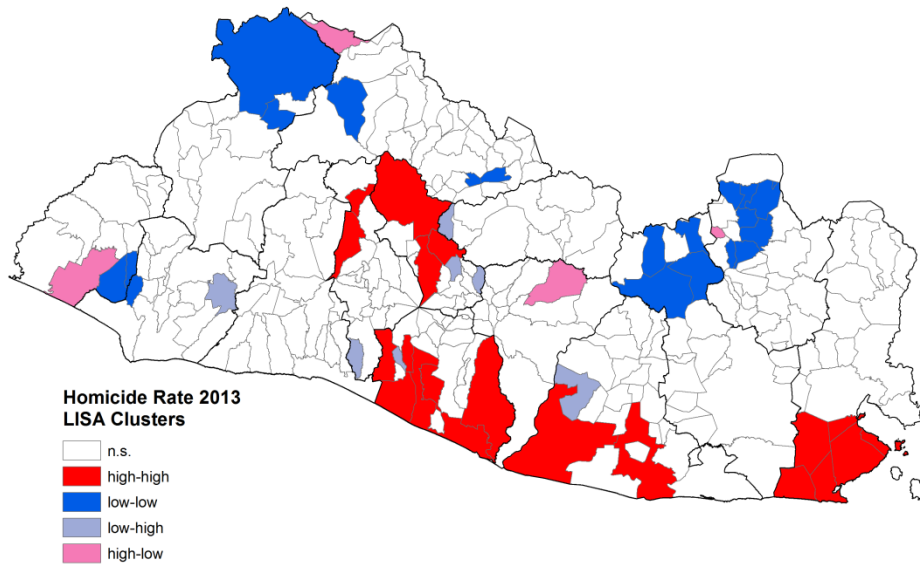
Table 2 reports the municipalities with the highest LISA values that are also statistically significant. Thus, from among all the red, high-high clusters in Figure 10, the table identifies the municipalities that perhaps most merit attention. The municipal code in the first column also helps identify the relevant department. For three-digit codes, the first digit is the department code; for four-digit codes, the first two digits are the department code.

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<sup>47</sup> Anselin, Luc. 2005. "Exploring Spatial Data with GeoDa: A Workbook." 146.



**Figure 9. LISA Map of Homicide Rates in 2013 (departments).**

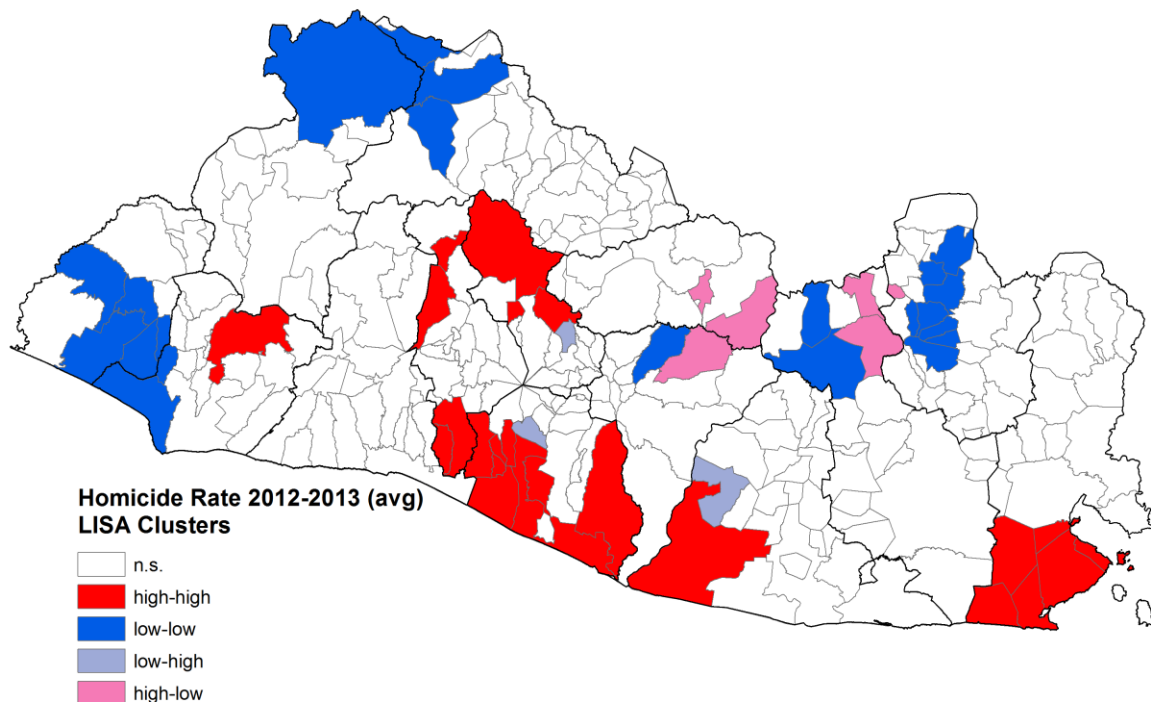


**Figure 10. LISA Map of Homicide Rates in 2013 (municipalities).**

<b>Code</b>	<b>Municipality</b>	<b>LISA</b>	<b>Sig</b>
822	San Luis La Herradura	4.54	0.0002
802	El Rosario	2.71	0.0014
1404	Conchagua	2.42	0.0290
815	San Pedro Masahuat	2.38	0.0056
1408	La Union	2.08	0.0496

Taken together, Figure 10 and Table 2 help identify the municipalities that constitute cores of clusters of violence, and also the departments that most deserve attention. From Table 2, the departments that stand out are La Paz (code = 8) and La Union (code = 14). Note that these are not the same departments identified in Figure 9 using a departmental-level of analysis.

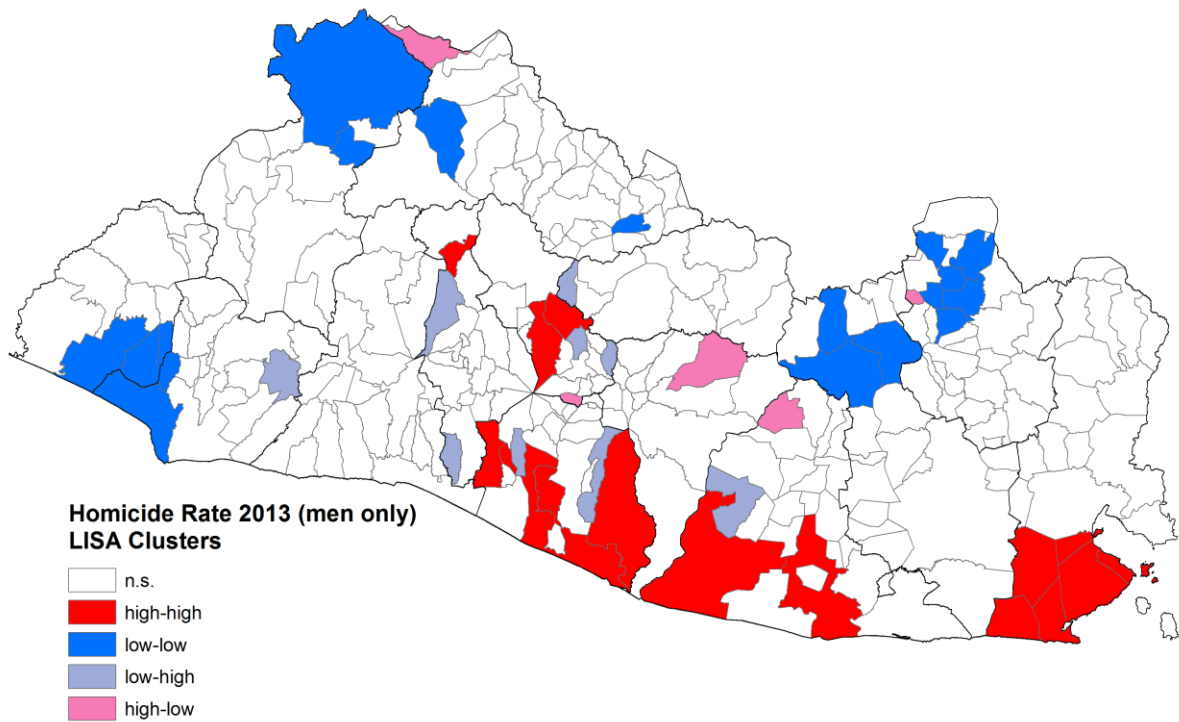
Figure 11 and Table 3 do the same for the average homicide rates from 2012-13. The same general pattern remains for violence clusters in the LISA map, and the Table again identifies the same five municipalities in the same two departments.



**Figure 11. LISA Map of Homicide Rates in 2012-2013.**

<b>Code</b>	<b>Municipality</b>	<b>LISA</b>	<b>Sig</b>
822	San Luis La Herradura	4.22	0.0002
1408	La Union	3.68	0.0192
815	San Pedro Masahuat	3.39	0.0058
1404	Conchagua	3.23	0.0026
802	El Rosario	2.56	0.0006

Disaggregating the overall homicide rates, Figure 12 and Table 4 do the same analysis for homicide rates in 2013 of men only. With some minor differences, the overall pattern appears to be the same and the information conveyed in Table 4 is also the same, suggesting that overall homicide rates are driven primarily by the homicides of men, i.e., male victims.

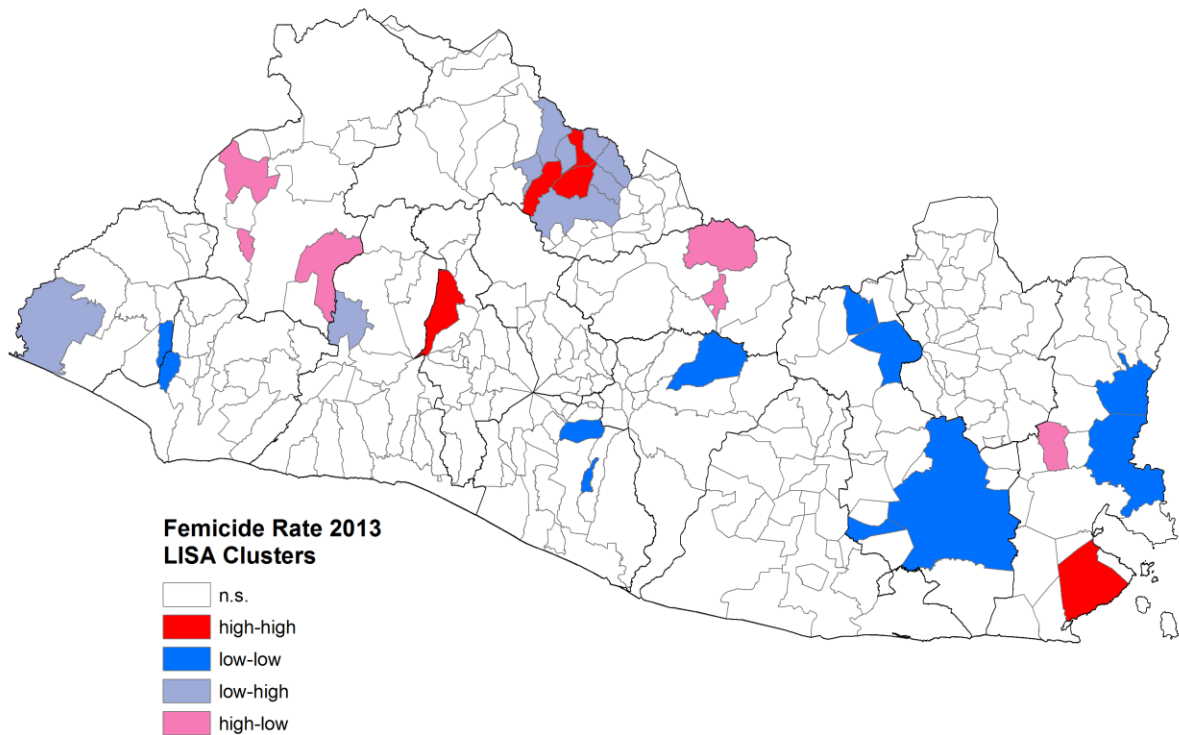


**Figure 12. LISA Map of Homicide Rates in 2013, Men Only.**



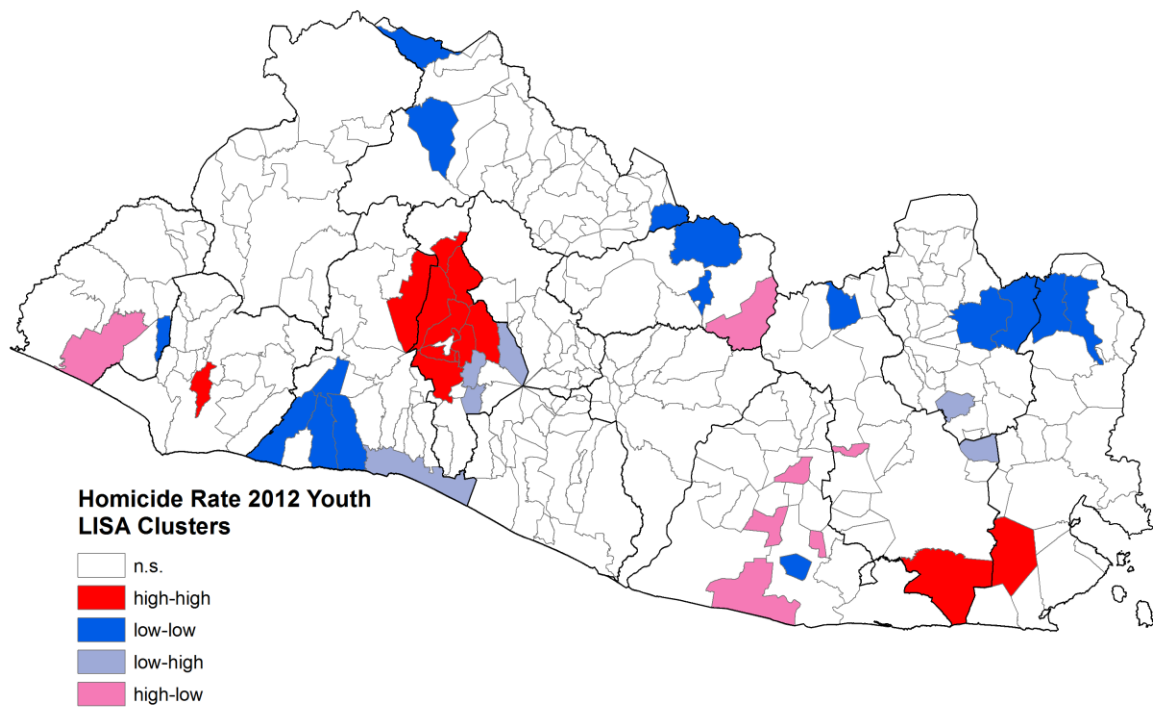
<b>code</b>	<b>Municipality</b>	<b>LISA</b>	<b>Sig</b>
822	San Luis La Herradura	5.14	0.0002
802	El Rosario	3.42	0.0004
815	San Pedro Masahuat	2.58	0.0064
1404	Conchagua	2.16	0.0368
1408	La Union	2.06	0.0408

Disaggregating further, Figure 13 and Table 5 report the same LISA map and top five municipalities, respectively, for femicides in 2013. Here the pattern is dramatically different. There is a set of three contiguous municipalities that constitute a high-violence cluster in the northern department of Chalatenango (code = 4), along the border with Honduras. There is another cluster core in the department of San Salvador, just north of the nation's capital, and a final cluster core in the southeastern department of La Union.



**Figure 13. LISA Map of Homicide Rates in 2013, Women Only.**

<b>Table 5. Municipalities with top 5 significant LISA values for 2013 homicide rates (women).</b>			
<b>Code</b>	<b>Municipality</b>	<b>LISA</b>	<b>Sig</b>
411	La Laguna	6.75	0.0046
406	Concepcion Quzaltepeque	5.48	0.0116
432	Santa Rita	4.20	0.0050
1404	Conchagua	0.88	0.0440
609	Nejapa	0.62	0.0350



**Figure 14. LISA Map of Homicide Rates in 2012, Youth Only.**

<b>Code</b>	<b>Municipality</b>	<b>LISA</b>	<b>Sig</b>
309	Nahulingo	7.52	0.0426
609	Nejapa	2.32	0.0434
602	Apopa	2.14	0.0038
618	Tonacatepeque	1.54	0.0282
601	Aguilares	0.93	0.0438

Lastly, Figure 14 and Table 6 repeat the previous LISA cluster analysis for youth homicides in 2012. As was the case with femicides, the pattern is very different from the aggregate homicide rate or the rate for homicides of only men. The dominant result for youth homicides is that these homicides are heavily concentrated in and around the nation's capital, covering much of the department of San Salvador, and extending into the neighboring departments of La Libertad to the west and Cuscatlan to the east. The municipality with highest LISA value is in a different department Sonsonate (the single red municipality in the western of the country; code = 3). However, all remaining municipalities in the top five are in the department of San Salvador. The nation's capital city, San Salvador, is not listed here but it is the eleventh highest LISA value, and is statistically significant (LISA value of 0.35, p-value of 0.0168).

## **4.2. Results 2: Spatial Regression**

While a full explanatory analysis of the varieties of homicide in El Salvador is beyond the scope of this paper, we offer the results of one explanatory model of the aggregate measure of all homicides for 2013. Here, we leverage the theoretical discussion of explanatory factors outlined in a previous section, as well as the variables described in the section on Data and Methods.

Table 7 reports two regression models: Models 1 and 2. Model 1 is an ordinary least-squares (OLS) regression with no spatial effects.<sup>48</sup> This baseline model reports three main results: (1) population pressures exert a positive, statistically significant, and theoretically expected effect on homicide rates; (2) extreme poverty exerts a negative, statistically significant and unexpected effect; and (3) education (composite measure) exerts a negative, statistically significant, and expected effect. Separately, the regression shows that many standard predictors of violence are not statistically significant in El Salvador's municipalities, including income, economic activity (age 15 and up), and security capacity (composite measure).

Lagrange multiplier (LM) tests (Anselin 1988) help identify the correct specification of a spatial regression in order to more accurately account for the spatial effects. The LM lag test

<sup>48</sup> All analyses conducted in R with the *spdep* package (Bivand 2002).

(7.26,  $p=0.007$ ) reported a higher value and more significance than the LM error test (4.30,  $p=.03$ ), suggesting a lag specification ( $y = \rho W y + X\beta + \varepsilon$ ; see equation 1 and discussion above). Also, robust LM tests show robust error test is not significant, while robust lag test is still significant at 0.05 level, confirming the lag specification.

Examining the p-values reveals that population density is no longer significant at the .05 or even .10 level, but the other three results from the OLS regression remain, supporting the validity of the conclusions. Specifically, population size has the expected positive effect on homicide rates, extreme poverty has an unexpected negative effect, and education has the expected negative effect. Further, the spatial lag of homicide rates is positive and statistically significant, indicating that an increase in homicide in neighboring communities has the effect of increasing homicide in one's home community. Reversing the transformation of the logged variable reveals that a one percent increase in homicide rates in nearby communities causes a 1.26 percent increase in homicide in a focal community.

**Table 7. OLS and Spatial Lag Regressions (DV = homicide rate, 2013, logged)**

	Model 1			Model 2		
	coef.	s.e.	p	coef.	s.e.	p
(Intercept)	-0.97	4.81	0.840	-0.74	4.60	0.872
Population	0.25	0.13	0.051	0.22	0.12	0.068
Population Density	0.24	0.14	0.082	0.19	0.13	0.140
Median Age	0.02	0.06	0.736	0.01	0.06	0.801
% Young Males	0.01	0.10	0.930	0.01	0.10	0.954
% Indigenous	-0.02	0.05	0.775	-0.02	0.05	0.764
% Rural	0.01	0.01	0.274	0.01	0.01	0.340
% Female HH	-0.02	0.02	0.281	-0.02	0.02	0.288
Income/cap	0.08	0.43	0.853	0.05	0.41	0.911
% Extreme Poverty	-0.04	0.01	0.005	-0.03	0.01	0.013
Education	-0.36	0.15	0.014	-0.30	0.14	0.033
% Unemployment	0.06	0.17	0.716	0.09	0.17	0.590
Economic Activity	0.00	0.01	0.720	0.00	0.01	0.939
Security Capacity	0.04	0.10	0.718	0.04	0.09	0.665
Rho ( $\rho$ )				0.23	.08	.009
N	261			261		
Adj. R-squared	0.22			.		
Wald	.			7.47		
AIC	919.48			914.59		
LM test	4.30			1.37		
p-value	0.04			0.24		

## 5. Conclusions and Policy Implications

Taken together, the cluster analysis and spatial regression generate the following conclusions.

- **Level of analysis:**  
Analysts should consider differences in data at municipal and departmental levels of analysis, along with the ways in which analysis of municipal-level data can lead to richer interpretations and improved targeting of violence-reduction policies.
- **Spatial clustering:**  
Various forms of homicide – aggregate, women only, men only, or youth only – cluster in non-random ways, i.e., these phenomena are not distributed randomly across El Salvador’s municipalities. Moreover, each type of homicide follows a different pattern of geographic distribution. Aggregate homicide rates and homicides of men show similar patterns, with clusters of violence along coastal communities and in central communities north of the capital. Femicides are clustered primarily in a set of municipalities in the northern department of Chalatenango. Youth homicides cluster dramatically in and around the nation’s capital, especially to the north of the city, and extending into the northeastern part of the department of La Libertad and to the northwestern part of the department of Cuscatlan.
- **Explaining homicide rates:**  
Many traditional predictors of violence do not appear to explain variation in aggregate homicide rates in El Salvador’s municipalities, including measures of family disruption, income, ethnic heterogeneity, and urbanization. Notably, measures of security capacity also do not have a statistically significant relationship with violence. In other studies of police presence, statistically significant results often suffer from an endogeneity problem. That is, police are frequently deployed to areas of high crime, so a positive association between high crime and police presence does not resolve the question of whether police presence causes high crime or high crime causes police presence.<sup>49</sup> This endogeneity is not addressed here. Still, the endogeneity problem is perhaps most acute when interpreting statistically significant results. Thus, the absence of any significant result with any of the available measures of police capacity is not good news given the level of attention dedicated to this particular policy option.
- **Population pressures, poverty and education**

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Rafael Di Tella and Ernesto Schargrodsy (2004). “Do Police Reduce Crime? Estimates Using the Allocation of Police Forces After a Terrorist Attack.” *American Economic Review* (March) 94(1): 115-133.

Population pressures, primarily in the form of population size, have an expected positive effect on homicide rates. As population increases, homicide rates increase.

Poverty has an unexpected, counterintuitive, negative relationship with homicide rates. That is, as poverty rates increase, homicide decreases. This finding cuts against a wide range of existing research. One possible explanation follows the logic of alternative hypotheses regarding economic activity. Specifically, while economic activity is generally expected to have a negative relationship with homicide, some research has found a positive relationship, suggesting that as economic activity increases, people interact more frequently, and there are more opportunities or targets for crime and violence. Following this logic, as poverty deepens, there may be fewer opportunities or targets for crime and violence, resulting in the finding reported here.

The education finding reinforces much of the findings about the protective effect of education found elsewhere in the literature, including in other countries in Latin America.<sup>50</sup>

- Lastly, violence has a neighborhood effect. That is, violence in one municipality influences violence in neighboring municipalities. This neighborhood or proximity effect is captured by the spatial lag in the last regression. Specifically, a 1 percent increase in the homicide rates of nearby municipalities is associated with a 1.26 percent increase in the homicide rate of a focal municipality.

Policy implications that derive from these conclusions include the following:

- Policymakers should target violence prevention policies in regional fashion, not at isolated communities. For instance, combining the findings from the LISA map in Figure 14 with the findings from the spatial regression, it appears a policy aimed at reducing youth violence in the city of San Salvador is unlikely to succeed if this policy is aimed only at that one city, ignoring the violence in adjoining municipalities.
- There is a high return on investments in education, even in comparison to short-term cost savings of hiring additional police.<sup>51</sup> This is perhaps particularly true given the results in El Salvador presented here, since there is strong evidence regarding the protective effect of education but no evidence of any beneficial effect of additional police personnel or additional police expenditures.
- Policymakers should also take a longer-term view. Educational investment pays off in short term by keeping youths in safe, productive, supervised environments,

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<sup>50</sup> e.g., Ingram, “Community Resilience to Violence: Local Schools, Regional Economies, and Homicide in Mexico’s Municipalities.”

<sup>51</sup> Lochner and Moretti, “The Effect of Education on Crime: Evidence from Prison Inmates, Arrests, and Self-Reports,” 182-183.

but it also pays off in manifold ways over the longer term as individuals with more education obtain better jobs and are less likely to risk the punitive sanctions of criminal behavior.

### **Author's Biographies**

**Matthew C. Ingram** is an assistant professor in the Department of Political Science at the University at Albany, SUNY. His research examines justice sector reforms, judicial behavior, and violence in Latin America. Ingram studies the political origins of institutional change and judicial behavior in the region's justice systems, focusing on subnational courts in Brazil and Mexico. He draws also on a family history in Mexico (dual citizen, U.S. and Mexico), extensive fieldwork in Latin America, and seven years of professional experience in law enforcement in California. Ingram's academic work has appeared in several peer-reviewed journals and edited volumes. He is completing a book project, "Crafting Courts in New Democracies," that presents his research on Mexico and Brazil. Ingram has held postdoctoral fellowships at UC San Diego's Center for U.S.-Mexican Studies (2009-2010) and Notre Dame's Kellogg Institute (2011-2012). He was also an assistant professor of political science at the University of Massachusetts, Dartmouth (2010-2011). He holds a law degree (2006) and a Ph.D. in political science (2009) from the University of New Mexico.

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