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405

May
2015

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GEOGRAPHIES OF VIOLENCE: A SPATIAL ANALYSIS OF FIVE TYPES OF HOMICIDE IN BRAZIL'S MUNICIPALITIES

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Working Paper #405 – May 2015

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*An earlier version of the cluster analysis and a summarized version of results appeared as a policy brief with the Brookings Institution on October 3, 2014. We thank two anonymous reviewers, Harold Trinkunas, Emily Miller, Karise Curtis, and participants in the Thursday policy seminar at Rockefeller College for helpful comments. Portions of this research were funded by the Rockefeller College Research Incentive Fund and the CSDA at the University at Albany. Please direct all correspondence to: mingram@albany.edu.

ABSTRACT

Objectives: Examine the spatial distribution of five types of homicide across Brazil's 5,562 municipalities and test the effects of family disruption, marginalization, poverty-reduction programs, environmental degradation, and the geographic diffusion of violence.
Methods: Cluster analysis and spatial error, spatial lag, and geographically-weighted regressions.
Results: Maps visualize clusters of high and low rates of different types of homicide. Core results from spatial regressions show that some predictors have uniform or stationary effects across all units, while other predictors have uneven, non-stationary effects. Among stationary effects, family disruption has a harmful effect across all types of homicide except femicide, and environmental degradation has a harmful effect, increasing the rates of femicide, gun-related, youth, and nonwhite homicides. Among non-stationary effects, marginalization has a harmful effect across all measures of homicide but poses the greatest danger to nonwhite populations in the northern part of Brazil; the poverty-reduction program Bolsa Família has a protective, negative effect for most types of homicides, especially for gun-related, youth, and nonwhite homicides. Lastly, homicide in nearby communities increases the likelihood of homicide in one's home community, and this holds across all types of homicide. The diffusion effect also varies across geographic areas; the danger posed by nearby violence is strongest in the Amazon region and in a large section of the eastern coast.
Conclusions: Findings help identify the content of violence-reduction policies, how to prioritize different components of these policies, and how to target these policies by type of homicide and geographic area for maximum effect.

RESUMO

Objetivos: Examinar a distribuição espacial de cinco tipos de homicídio em 5562 municípios brasileiros e testar o efeito de desagregação familiar, marginalização, programas de redução da pobreza, degradação ambiental e a difusão geográfica da violência.
Métodos: Análise de clusters, modelo espacial autoregressivo (spatial lag), modelo de erro espacial (spatial error) e regressão geográfica ponderada (geographically weighted regression)
Resultados: Mapas identificam clusters de alta e baixa taxa de diferentes tipos de homicídio. Os resultados principais das regressões espaciais mostram que algumas variáveis independentes têm efeitos uniformes e estacionários ao longo de todos os municípios, enquanto outras variáveis independentes possuem efeitos não uniformes e não estacionários. Entre as variáveis com efeito estacionário, desagregação familiar possui efeito nocivo para todos os tipos de homicídio, exceto femicídios, e degradação ambiental tem efeito prejudicial, aumentando as taxas de femicídio, homicídios com o uso de armas, homicídios de jovens e de não brancos. Entre variáveis com efeitos não estacionários, marginalização tem efeito prejudicial para todos os tipos de homicídio, mas representa maiores riscos para não brancos no Nordeste do Brasil; o programa Bolsa Família tem efeito protetor, reduzindo a maioria dos tipos de homicídio, especialmente relacionados a armas, jovens e não brancos. Por fim, homicídios em comunidades próximas aumentam a probabilidade de homicídios em uma determinada comunidade, o que vale para todos os tipos de homicídio. O efeito de difusão também varia em diferentes áreas: o perigo representado pela violência próxima é mais forte na região amazônica e na costa leste.

Conclusões: Os resultados ajudam a identificar o conteúdo de políticas de redução da violência, como priorizar diferentes componentes dessas políticas e como direcionar essas políticas por tipo de homicídio e área geográfica para um máximo efeito.

INTRODUCTION

Violence in Latin America generates heavy human, economic, social, and political costs for individuals, communities, and societies. A particularly pernicious effect of violence is that it undermines citizens' confidence in democracy and in their own government. Responding to public fear, politicians across the region have adopted a wide range of policy responses to violence, ranging from militarizing public security, to "mano dura" crack downs, to negotiating truces with organized crime, to decriminalizing illicit economic activity. Although many of these policies are politically expedient, few are based on evidence of how public policy actually affects rates of violence (Bailey and Dammert 2006, 250–51).

By contrast, this paper examines the origins of violence clusters within a country—Brazil—offering a spatial analysis of how violence clusters geographically, how predictors of violence vary in their effect across territorial units, and how violence diffuses among those units. In doing so, this study shows how public policies affect violence and how these policies might be further tailored to have greater impact. Brazil provides a particularly useful case for examining the effectiveness of violence-reduction strategies because of the availability of comparable data collected systematically across 5,562 municipal units. This allows for an explicitly spatial approach to examining geographic patterns of violence—how violence in one municipality is related to violence in neighboring municipalities, and how predictors of violence are also conditioned by geography. The key added value of the spatial perspective is that it addresses the dependent structure of the data, accounting for the fact that units of analysis (here, municipalities) are connected to each other geographically and that what happens in nearby units may have a meaningful impact on the outcome of interest in a home, focal unit. Thus, the spatial approach is better able to examine compelling phenomena like the spread, diffusion, or spillover of violence across units.

Disaggregating the outcome of interest, we visualize data on five types of homicide—aggregate homicides, homicides of women ("femicides"), firearm-related homicides, youth homicides (ages 15–29), and homicides of victims identified by race as either black or brown (mulatto), i.e., nonwhite victims—all for 2011, presenting these data in maps. We adopt a municipal level of analysis and include homicide data from 2011 for the entire country, i.e., on all 5,562 municipalities across twenty-seven states (including the Federal District). This allows us to develop maps that identify specific municipalities that constitute cores of statistically significant clusters of violence for each type of homicide. These clusters offer a useful tool for targeting policies aimed at reducing violence. We then develop an analysis based on spatial regression models, using predictors from the 2010 census and other official sources in Brazil, culminating with a geographically weighted regression (GWR) that examines how the significance, direction, and magnitude of predictors of violence—including the diffusion effect—vary across space. While GWR has been widely used to examine how explanatory variables may have an unstable, i.e., non-stationary, effect on an outcome of interest across all spatial units, the analysis of the locally varying effect of diffusion itself is relatively new (see Shoff, Chen, and Yang 2014).

Existing research on homicide and violence in Brazil adopts different methods, including ethnographic investigations (e.g., Caldeira and Holston 1999; Penglase 2005; Willis 2014) and quantitative methods, especially regression models using panel data (e.g., Cardia, Adorno, and Poleto 2003; De Souza et al. 2007; Lance 2014; Reichenheim et al. 2011). Our approach is closest to others employing a spatial perspective (e.g., Carvalho, De Castro Cerqueira, and Lobão 2005; Ceccato 2005; Santos, Barcellos, and Sá Carvalho 2006) or combinations of ethnography with spatial analysis (Barcellos and Zaluar 2014)). However, even among spatial analyses, most existing research focuses on either individual cities or larger metropolitan areas (e.g., Barcellos and Zaluar 2014; Caldeira and Holston 1999; Ceccato 2005; Penglase 2005; Santos, Barcellos, and Sá Carvalho 2006). A smaller set of quantitative studies adopts a state level of analysis, e.g., De Souza et al. (2007) who also consider state capitals in their model. To our knowledge, only two studies examine violence across all Brazilian municipalities (Carvalho, De Castro Cerqueira, and Lobão 2005; Lance 2014), and of these, only Carvalho, De Castro Cerqueira, and Lobão (2005) do so from a spatial perspective. Thus, our findings update and build on Carvalho, De Castro Cerqueira, and Lobão (2005), and also provide a spatial complement to the nonspatial findings in Lance (2014).

The paper proceeds as follows. First, we motivate the analysis by outlining the multiple harms associated with violence. Next, we closely examine subnational patterns of variation in homicide. We visualize data on five types of homicide, presenting these data in maps. This section includes an exploratory spatial analysis of the data just mapped, testing whether the various types of homicide are distributed in a spatially random manner across Brazil's 5,562 municipalities. Again, the benefits of a municipal level of analysis emerge, and the section identifies specific municipalities that constitute cores of statistically significant clusters of violence for each type of homicide. These clusters offer one useful tool for targeting policies aimed at reducing violence. In the third section we add an explanatory analysis based on a spatial regression models and using predictors from the 2010 census. This section proceeds in two phases: (a) testing existing theories using basic spatial model specifications, and (b) leveraging diagnostics and GWR techniques, testing for the uneven effect of predictors of interest and of the diffusion of violence.

Core results show that some predictors have uniform or stationary effects across all units, while other predictors have uneven, non-stationary effects. Among the stationary effects, key findings include the following: family disruption, captured by the percentage of women with no education who are heads of households and have kids under age 15, has a harmful effect across all types of homicide except femicides; and environmental degradation has a harmful effect on women in that there is a strong positive association between development projects with environmental impact (EI) and the femicide rate, but EI is also consistently harmful for gun-related, youth, and nonwhite homicides. Among non-stationary, locally varying effects, the main findings include the following: marginalization—a composite measure including indicators of poverty, illiteracy, and rurality—has a harmful effect across all measures of homicide, but poses the greatest danger to nonwhite populations in the northern part of Brazil; and the proportion of poor, eligible families covered by Bolsa Família (BF coverage) has a protective, negative effect for most types of homicides, but the findings are most consistent for gun-related, youth, and nonwhite homicides. Among explicitly spatial results, key findings include the fact that different types of homicide cluster geographically; homicide in nearby communities increases the likelihood of homicide in one's home, focal community, and this holds across all types of homicide; and the effect of homicide in nearby areas—the diffusion effect—also varies across geographic areas, i.e., it is non-stationary. Specifically, the danger posed by nearby violence is strongest in the Amazon region and in a large section of the eastern coast, spanning from Espírito Santo to the northeastern states of Sergipe and Alagoas.

Lastly, the conclusion revisits the main findings and discusses policy implications. Specifically, the findings help identify the content of violence-reduction policies, how to prioritize different components of these policies, and how to target these policies for maximum effect across different types of homicide and across geographic units.

THE MULTIPLE HARMS OF VIOLENCE

Violence directly affects individual and communities and is also increasingly understood to undercut political and economic 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 (Sarles 2001; Cruz 2008). Indeed, in some new democracies in Latin America, frustration with criminal violence has led majorities to support a return to authoritarian government (Cruz 2008, 241). Further, a 2011 poll in Mexico found more than a quarter of respondents willing to support a candidate tied to organized crime for the sake of peace and security (Benítez Manaut 2012, 57, cited in Schedler 2014, 14). Across the region, polls identify crime and citizen security as top policy priorities (Lagos and Dammert 2012). Thus, the prevention and reduction of violence is crucial to democratic stability and institutions.

Violence also generates heavy economic costs, dampening development, due both to its direct and indirect costs. Direct costs can include expenses due to injury or property damage; indirect costs can include increased insurance costs for commerce or transport, reduced work hours, or reduced traffic and movement of people due to fear and insecurity. In the United States, 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 GDP in Brazil, 5 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 (Londoño and Guerrero 1999; Buvinic and Morrison 1999, cited in WHO 2002). 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 (Londoño and Guerrero 1999, 26; also Ayres 1998, cited in Mesquita Neto 2005, 49). In 2004, violence in Brazil was estimated to cost the public sector US $9.6 billion, with a total cost for society—including some of the indirect costs outlined above—of almost US $30 billion (Reichenheim et al. 2011). Given Brazil's total GDP that year of US $663,760,341,880 (World Bank 2014), violence cost 4.5 percent of GDP. Restating, violence routinely costs several countries, including Brazil, 4-10 percent of GDP. Given that GDP growth rates of 3–4 percent would be considered healthy, a substantial reduction of violence in these countries would have dramatic benefits for development (see also World Bank's 2006, 27, finding that a 10 percent reduction in homicide rates leads to a 0.7–2.9 percent increase in GDP over next five years). 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 also motivates this study. According to some estimates, Latin American holds 8 percent of the world's population but accounts for 42 percent of all homicides (Naim 2012). The United Nations Office on Drugs and Crime (UNODC 2014) reports homicide rates for the major regions of the world for the eighteen years from 1995–2012. 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 US homicide rate was 5 per 100,000 in 2010, the rate for Latin America was approaching 30 (see also Ingram and Curtis 2014; Ingram and Marchesini da Costa 2014).

Focusing on Brazil and its neighbors, Brazil's homicide rate closely tracks the broader regional rate from 2000–2012, while several countries fall below that, including Argentina, Chile, and Uruguay. However, Brazil's rate is consistently higher than the average rate for South America. The national homicide rate in Brazil increased from 2011 to 2012, from 23.4 to 25.2 per 100,000. Only two countries in South America have homicide rates higher than Brazil: Colombia and Venezuela. Brazil had homicide rates similar to those of the United States in the beginning of the 1980s, but by the end of that decade Brazil's rates had already doubled the American rates (Caldeira and Holston 1999). In the beginning of the 2000s, Brazil was already known as one of the countries with the highest homicide rates in the world (De Souza et al. 2007). Homicides are the main cause of death from external causes among men between fifteen and thirty-four years of age in some Brazilian cities, and overall homicide is only surpassed by cardiovascular diseases (Santos, Barcellos, and Sá Carvalho 2006). Also, in 2004, more than 70 percent of the homicides were committed using firearms (De Souza et al. 2007). State capitals concentrated nearly 40 percent of deaths by firearms, despite having only 24 percent of the Brazilian population (De Souza et al. 2007; see also Ingram and Marchesini da Costa 2014).

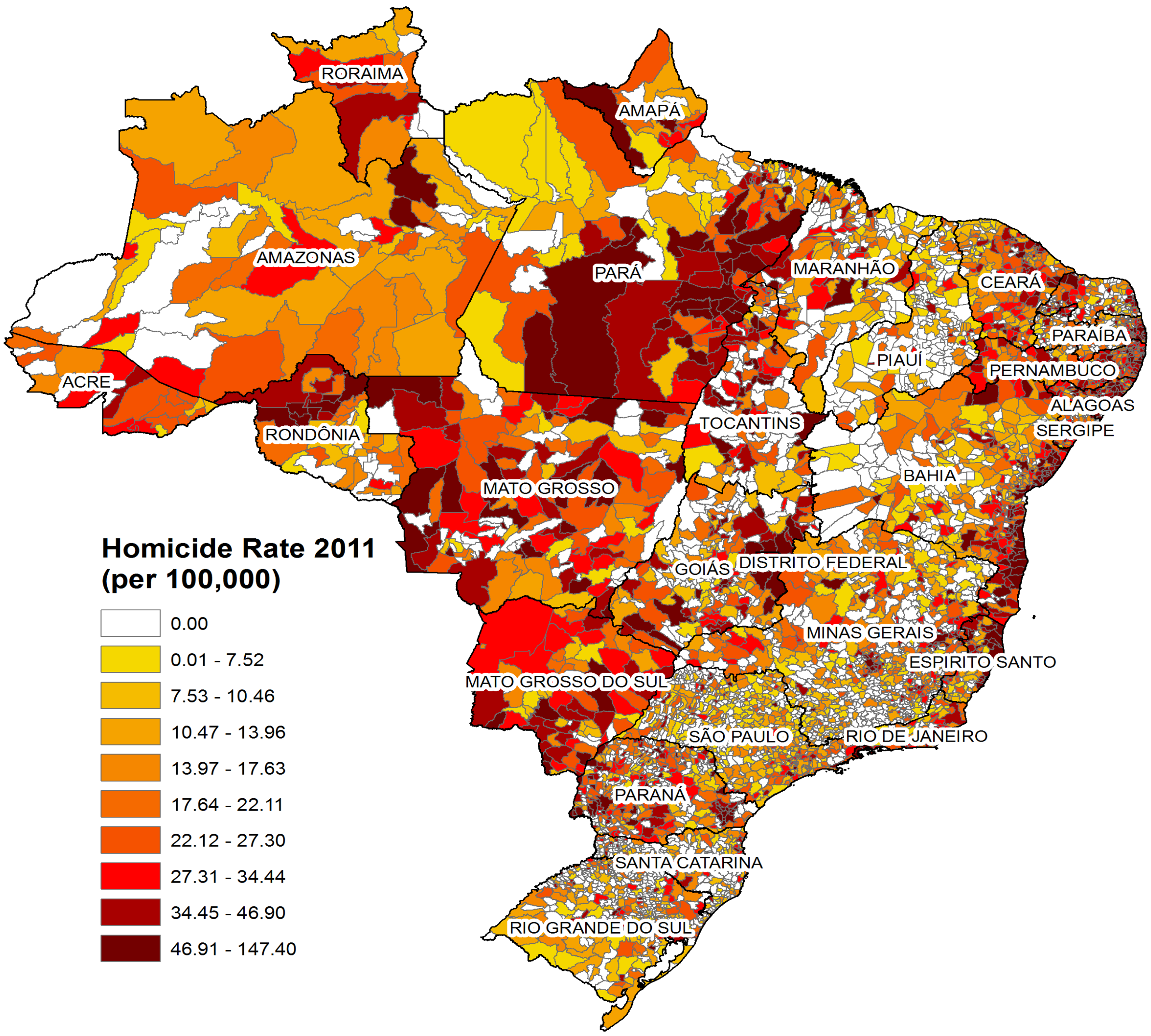
In sum, Latin America has an exceptionally high homicide rate compared with the rest of the world, and Brazil's national homicide rate closely tracks the regional rate. In other words, Brazil is neither on the high end of the distribution of homicide rates in the region nor is it on the low end of this distribution, so the country could be considered typical of this phenomenon in a region marked by elevated levels of violence. More than being typical of Latin American cases, Brazil's tremendous regional diversity enhances analytic leverage since subnational analysis of the Brazilian case allows for more controlled large-n comparisons, connecting the paper to the broader literature on the advantages of subnational analysis (Snyder 2001). Although diverse, Brazil's municipalities are under a similar institutional framework and share relatively similar cultural heritages, among other potential confounders. Lastly, Brazil is the region's largest country and largest economy, and existing research within Brazil notes a marked unevenness in the distribution of homicide, especially different types of homicides, in the country's urban areas.

HOMICIDE IN BRAZIL: AN EXPLORATORY ANALYSIS

Figure 1 reports a choropleth map of 2011 homicide rates (deciles) at the municipal level in Brazil. Lighter colors indicate low homicide rates, with white identifying those municipalities with no homicides and darker colors identifying high homicide rates. Even a cursory examination of this kind of map shows that violence is unevenly distributed across Brazil. Further, about 10 percent of Brazilian cities (541) have homicide rates above 40 and more than 5 percent of cities (312) have homicide rates above 50. Thus, at least in comparison with global and regional homicide rates, a very large number of Brazilian cities experience levels of violence far above any regional average and above most national averages. In comparison with the United States, where the highest municipal homicide rate hovers around 50 and only a handful of cities ever cross 40, Brazil has hundreds of cities that experience higher levels of violence than the worst US cities.

FIGURE 1

HOMICIDE RATES FOR 2011 IN BRAZIL'S MUNICIPALITIES



The exploratory analysis includes Figures 2–6, which report the results of cluster analyses of smoothed rates for different types of homicide.[1] The related tables (Tables 1–5) identify the municipalities with the top ten significant values of local indicators of spatial autocorrelation (LISA values: Anselin 1995) for each type of homicide. LISA values are a measure of the association between the homicide rate in one unit and the homicide rate in neighboring units. Each municipality has a different LISA value. The value is positive if the local homicide rate is high and the neighborhood rate is also high or if the local rate is low and the neighborhood rate is also low; in either case, a positive LISA value captures the clustering of similar values (high or low) of homicide rates. In contrast, a LISA value is negative if the local rate is high and the neighborhood rate is low or if the local rate is low and the neighborhood rate is high; in either case, a negative LISA value captures the clustering of dissimilar values. Permutation tests yield estimates of the statistical significance of these values.[2] Thus, LISA values convey meaningful information about the clustering of similar or dissimilar values and whether this clustering is substantially different from what we would expect by chance. Further, the average of all LISA values conveys the overall, countrywide spatial association of homicide rates; this global measure of association is known as Moran's *I*.[3]

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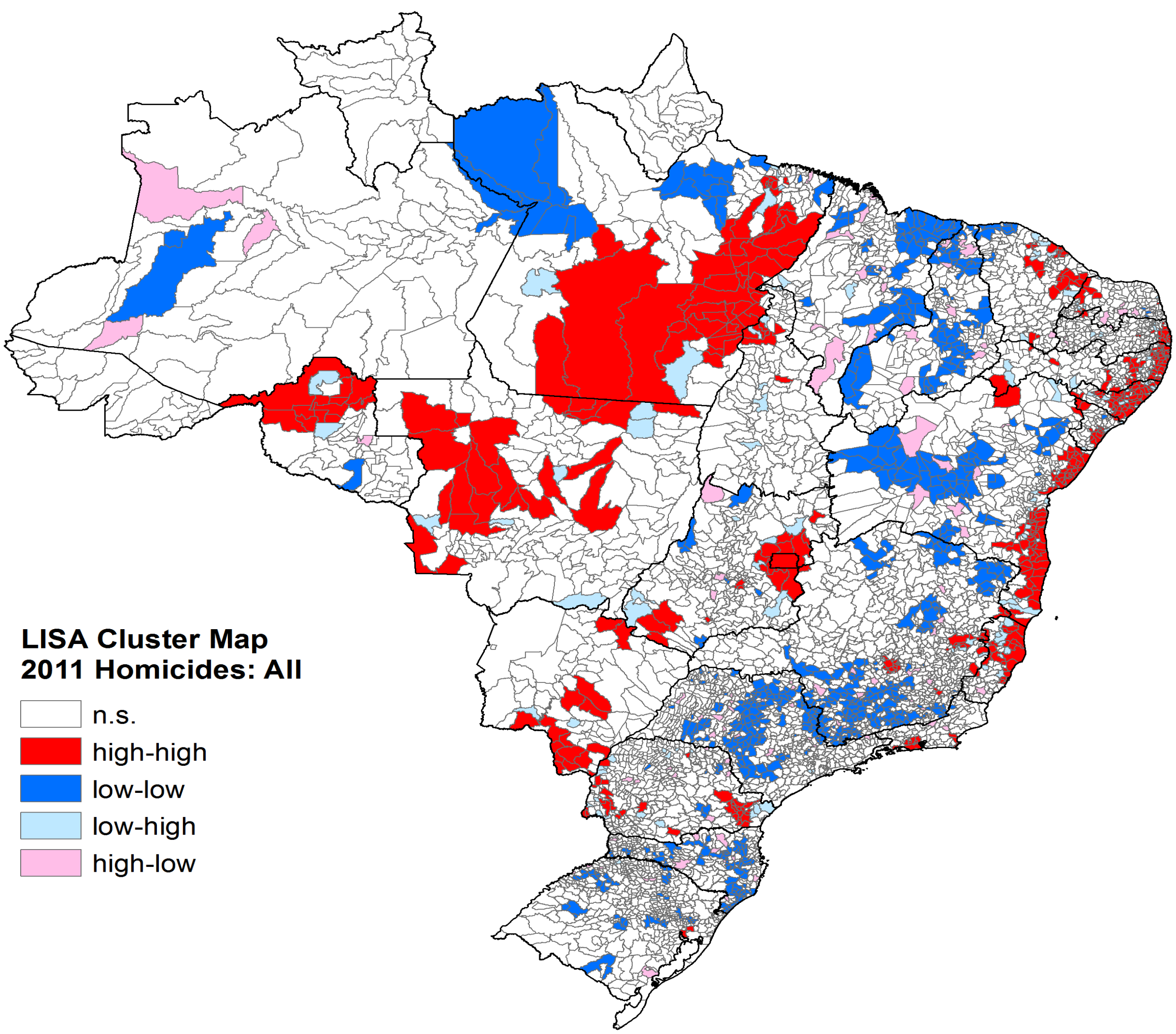
[1] Due to the large variation in the base population across Brazil's municipalities, the raw homicide rate can be deceptively high with a small number of homicides in units where the base population is low (denominator is low, inflating the risk calculation). Conversely, the rate can be deflated even with a large number of homicides where the base population is very large. Rate smoothing address this variance instability, adjusting the rate in units with small populations downward and the rate in units with large population upward based on the distribution of population across all units (see Assunção and Reis 1999; Anselin 2005). All LISA maps presented here include this smoothing.
[2] All estimates of statistical significance are based on at least 5,000 permutations using GeoDa.
[3] It should be noted that cluster analysis is sensitive to the manner in which spatial weights are specified. All of the reported findings use a first-order queen contiguity matrix to capture connectedness among units.

FIGURE 2

LISA CLUSTER MAP FOR ALL HOMICIDES



Every municipality that is colored in Figure 2 represents the core of a statistically significant cluster of homicide. Our primary analytic interest is in those units that are either red or blue. Red units are those where the homicide rate is unusually high and the rate is also unusually high in surrounding units (high-high clusters). Blue units are those where the homicide rate is low and is also low in surrounding units (low-low). Thus, in red units we see a high-high association of violence that is beyond what we would expect to see by chance, and in blue units we see a low-low association of violence that is also not what we would expect to see simply by chance. Notably, the colored units represent cores of these clusters, so the full cluster that exhibits this statistically significant association extends beyond the colored units to include all neighboring units.

Several large, high-high clusters are distributed throughout Brazil, including the area in and around the country's capital, Brasília, virtually all coastal municipalities from Espírito Santo to the northeastern part of the country, a large swath of municipalities in Pará and Maranhão, another large section of the states of Rondônia and Mato Grosso, and a large set of municipalities along the border with Paraguay and Argentina. Overall spatial association is high (Moran's I = 0.37; $p<.01$). However, we are more interested in local patterns of spatial autocorrelation, so LISA values help identify municipalities that are statistically significant cores of violence clusters. Table 1 identifies municipalities with top ten LISA values that are also statistically significant ($p<.05$).

Notably, the ten municipalities in Table 1—which represent only a fraction of the total of 5,562 municipalities—come from only three states, identified by the first two digits in the municipal code: Paraíba (code 25), Alagoas (27), and Bahia (29). One of these municipalities, João Pessoa, is the state capital of Paraíba. Further, all three of these states are from the northeast of Brazil. Thus, at this early stage of analysis, it appears the geographic association of high levels of violence is especially acute in the northeast of the country.

TABLE 1

MUNICIPALITIES WITH TOP 10 SIGNIFICANT LISA VALUES, ALL HOMICIDES

Mun. Code	Mun. Name	LISA	p
2930709	Simões Filho	31.40	.0001
2503209	Cabedelo	30.64	.0003
2919207	Lauro de Freitas	27.81	.0001
2707701	Rio Largo	26.36	.0001
2705200	Messias	23.56	.0001
2706901	Pilar	22.85	.0001
2905701	Camaçari	21.88	.0001
2704708	Marechal Deodoro	21.61	.0001
2507507	João Pessoa	20.75	.0001
2708907	Satuba	18.43	.0001

In general, the same pattern holds for homicides of men only as for all homicides. This is not surprising since most homicide victims are men. The overall spatial autocorrelation for men only remains high (Moran's $I = 0.38$; $p<.01$), and an examination of the largest significant LISA values (not reported here) identifies many of the same units as identified for all homicides. As was the case with all homicides, the top ten municipalities for homicides of men only come from the same three northeastern states: Paraíba, Alagoas, and Bahia. Two municipalities – João Pessoa and Maceió – are state capitals. Further, Marechal Deodoro and Rio Largo neighbor Maceió in Alagoas, Pilar neighbors Marechal Deodoro, and Messias neighbors Rio Largo. Combined with Satuba (previous table), the area in and around the state capital of Alagoas (Maceió) is a remarkable cluster of high levels of violence.

Figure 3 and Table 2 report the results for femicides. Even a quick glance at the LISA map shows that the pattern of geographic distribution of femicides departs from the patterns for all homicides, showing fewer and smaller clusters. The reduced amount of overall association between local violence and neighborhoods of violence is also reflected in the lower overall statistic (Moran's $I = 0.09$; $p<.01$). However, at a more localized level, some areas of concern remain—such as the large cluster around the nation's capital, or the smaller clusters near the international crossing into Paraguay at Foz de Iguaçu and Ciudad del Este. Also, new areas of concern emerge, such as the northwestern part of the state of Amazonas bordering Colombia (*cabeça do cachorro*, or "head of the dog"). This area near the international border is heavily militarized, and there is a persistent concern about human and sex trafficking, which would tend to be associated with violence against women. Indeed, on 2013 the federal police arrested nine people in a ring accused of sexual abuse of indigenous girls (Gabeira 2011; Brasil 2013). Further, a large portion of the state of Espírito Santo constitutes a cluster of high femicide rates, along with a large region north of the capital of Salvador in the state of Bahia.

Looking at Table 2, the municipalities with the top ten significant LISA values for femicides come from five states, identified by the first two digits in the municipal code: Paraíba (code 25), Bahia (29), Espírito Santo (32), Rio de Janeiro (33), and Goiás (52). Two state capitals are represented: Vitória (ES) and João Pessoa (PB).

TABLE 2

MUNICIPALITIES WITH TOP 10 SIGNIFICANT LISA VALUES, WOMEN ONLY (FEMICIDES)

Mun. Code	Mun. Name	LISA	p
2919207	Lauro de Freitas	19.83	.0001
2930709	Simões Filho	16.48	.0001
2503209	Cabedelo	16.21	.0002
3205309	Vitória	14.05	.0001
3205002	Serra	13.10	.0022
3300233	Armação dos Búzios	12.48	.0099
2507507	João Pessoa	12.01	.0006
2921005	Mata de São João	10.19	.0008
5212501	Luziânia	9.54	.0004
3205200	Vila Velha	7.15	.0048

FIGURE 3

LISA CLUSTER MAP OF HOMICIDES, WOMEN ONLY (FEMICIDES)

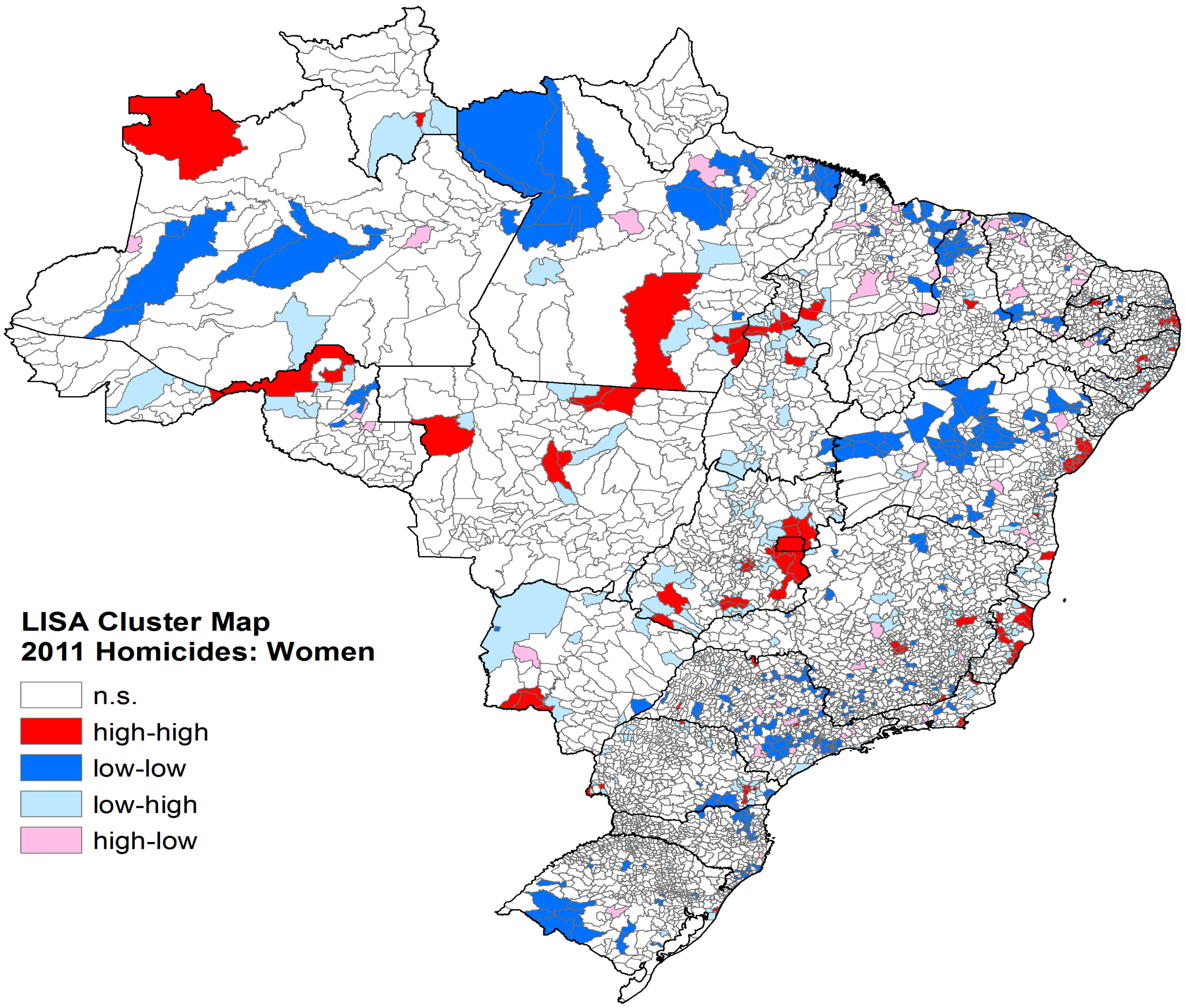


Figure 4 and Table 3 report the results for firearm-related homicides. Overall, there is more clustering than with femicides and even slightly more than with aggregate homicides or homicides of men only (Moran's $I = 0.40$; $p<0.01$). Thus far, then, gun-related homicides exhibit the highest amount of overall spatial association. Large regions of high levels of violence include the western part of the state of Pará and the northern part of Tocantins, the northern half of the state of Rondônia (and including adjoining areas in Amazonas), the region in and around the nation's capital, almost the entire eastern coastline from Paraíba to Espírito Santo. Several smaller areas are also compelling, including the area around Foz do Iguaçu in the state of Paraná, and the fact that a cluster of high violence surrounds the city of Rio de Janeiro but not São Paulo. As was the case with all homicides, the top ten LISA values are generated by cities in three states: Paraíba (25), Alagoas (27), and Bahia (29).

TABLE 3

MUNICIPALITIES WITH TOP 10 SIGNIFICANT LISA VALUES, FIREARMS ONLY

Mun. Code	**Mun. Name**	**LISA**	**p**
2503209	Cabedelo	47.61	.0001
2707701	Rio Largo	42.44	.0001
2705200	Messias	37.43	.0001
2930709	Simões Filho	37.19	.0001
2706901	Pilar	36.11	.0001
2919207	Lauro de Freitas	33.80	.0001
2507507	João Pessoa	33.34	.0001
2704708	Marechal Deodoro	30.80	.0001
2708907	Satuba	28.13	.0001
2905701	Camaçari	26.01	.0001

FIGURE 4

LISA CLUSTER MAP OF HOMICIDES, FIREARMS

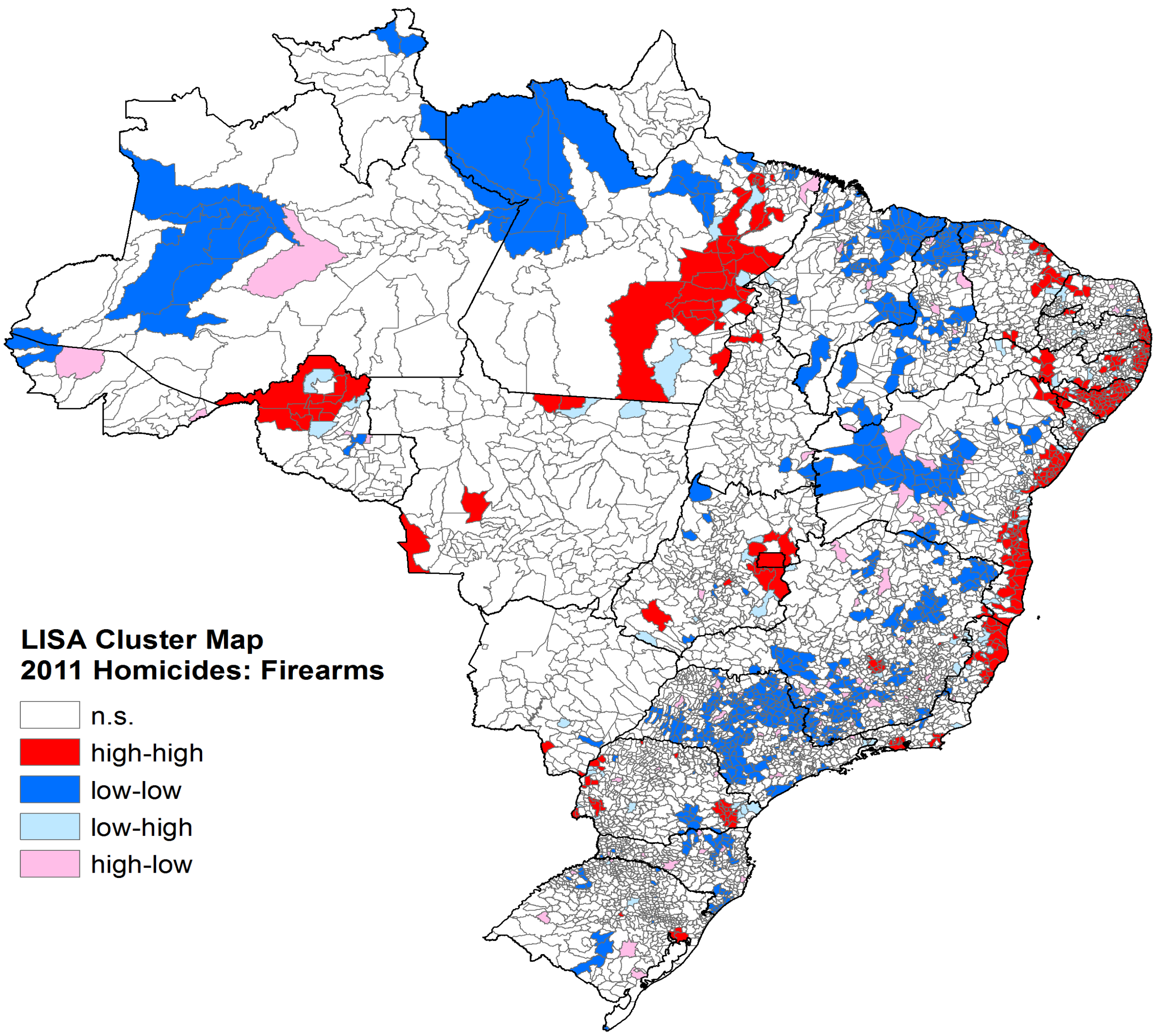


Figure 5 and Table 4 report the results for homicides of youth. Overall, there is substantial clustering (Moran's $I = 0.33$; $p<.001$). Local patterns mirror those seen with aggregate homicides and firearm-related homicides. Further, the top ten LISA values are generated by the same three states that generated these values for all homicides and gun-related ones: Paraíba, Alagoas, and Bahia. Moreover, the greater area around the capital of Alagoas, Maceió, continues to be represented heavily among these values, including the municipalities of Maceió, Marechal Deodoro, Pilar, Rio Largo, and Messias.

Turning to homicides of victims classified by race, we report the results for black and brown victims grouped together (i.e., nonwhite homicides). These data depend on figures for the base population—generated by self-reported racial characteristics in the census—and figures for homicide, hinging on racial characteristics reported by authorities. Given racial politics in Brazil, people might be less likely to self-identify as black than as brown, while authorities may be more likely to classify victims into darker categories (French 2013). These reporting tendencies may cause distortions in the data. Since our substantive interest is in the patterns of victimization among nonwhites, a fuller, more accurate accounting of nonwhite victims is likely to appear if we collapse the categories of black and brown together.

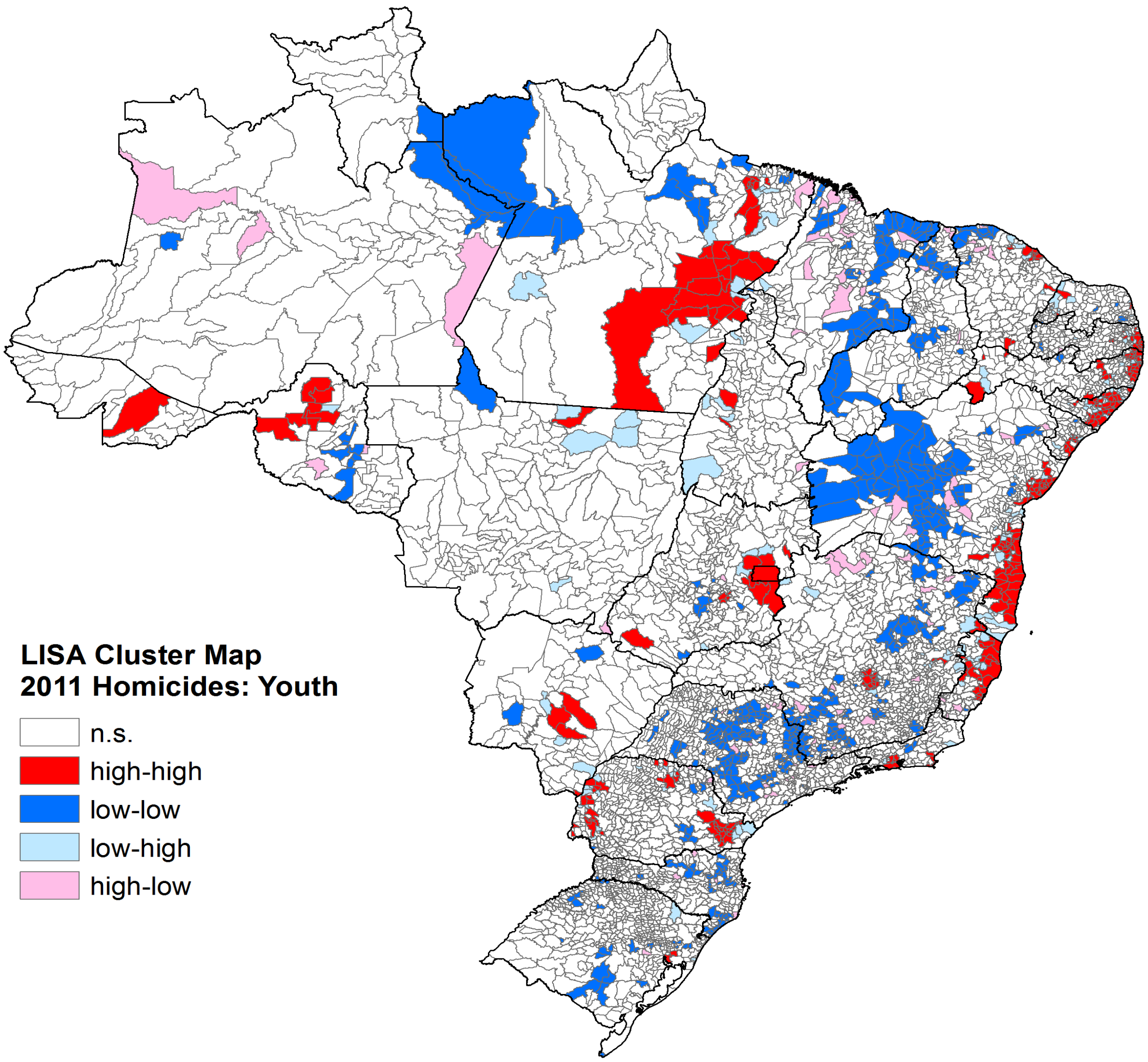
TABLE 4

MUNICIPALITIES WITH TOP 10 SIGNIFICANT LISA VALUES, YOUTH ONLY

Mun. Code	**Mun. Name**	**LISA**	**p**
2503209	Cabedelo	48.38	.0002
2919207	Lauro de Freitas	46.32	.0001
2930709	Simões Filho	45.31	.0001
2707701	Rio Largo	38.12	.0001
2705200	Messias	31.83	.0001
2507507	João Pessoa	29.94	.0001
2905701	Camaçari	29.82	.0001
2704708	Marechal Deodoro	29.64	.0001
2704302	Maceió	25.52	.0001
2706901	Pilar	24.50	.0001

FIGURE 5

LISA CLUSTER MAP OF HOMICIDES, YOUTH



Turning to the collapsed category of victims classified as black or brown, there is a higher level of overall spatial association (Moran's $I = 0.35$; $p<.01$). Locally, several of the same clustering patterns as previously observed with all homicides, gun-related homicides, or youth homicides appear, including a large region of high violence covering parts of and straddling the borders of Pará, Tocantins, and Mato Grosso, clusters of high violence spanning most of the eastern coastline, straddling borders of several states, a cluster in and around the city of Rio de Janeiro, and a substantial cluster around the nation's capital. Table 5 also reports the now familiar three states that generate the top ten LISA values for nonwhite homicide: Paraíba, Alagoas, and Bahia.

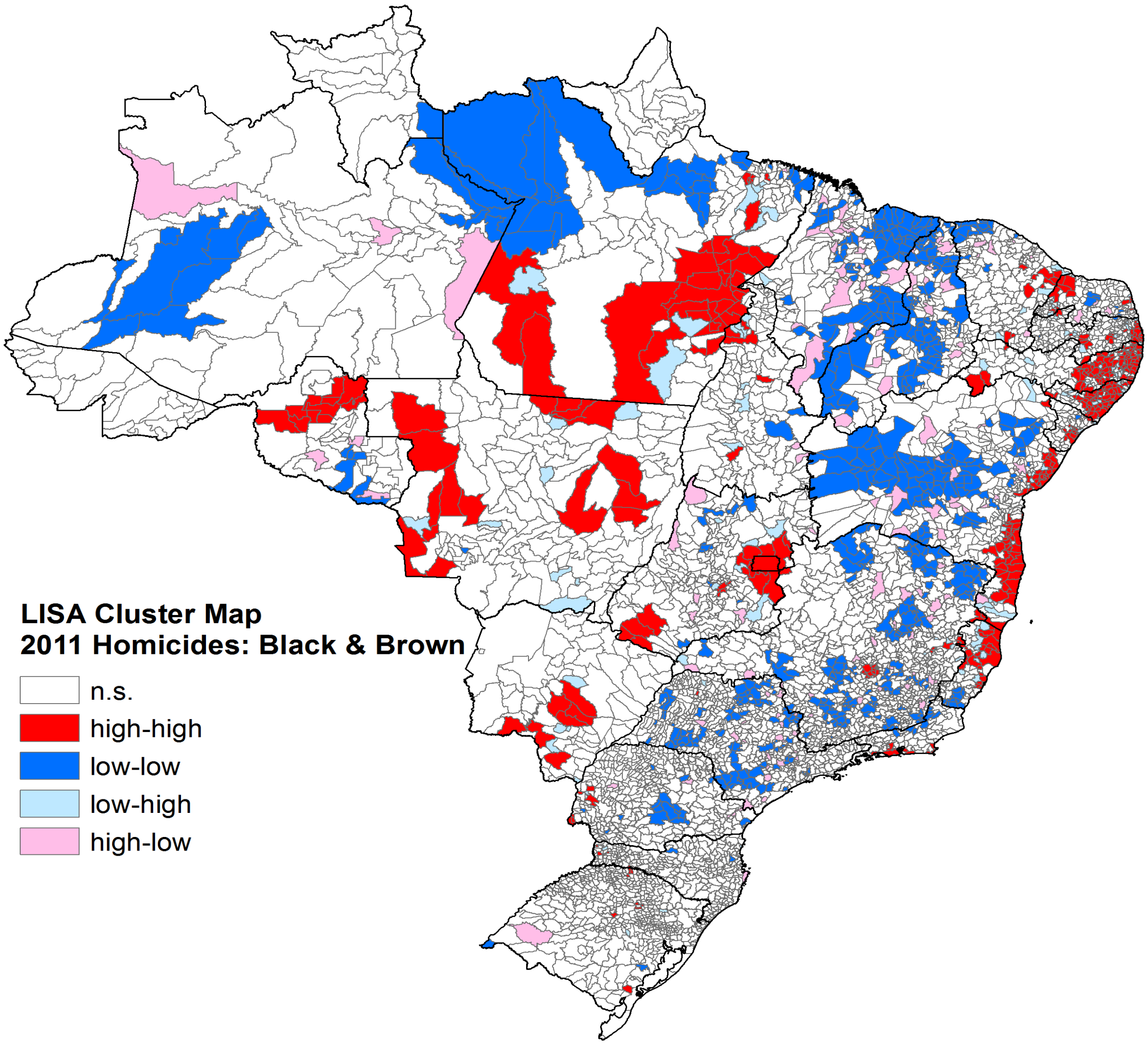
TABLE 5

MUNICIPALITIES WITH TOP 10 SIGNIFICANT LISA VALUES, BLACK AND BROWN ONLY

Mun. Code	Mun. Name	LISA	p
2503209	Cabedelo	51.10	.0001
2507507	João Pessoa	35.88	.0001
2707701	Rio Largo	30.23	.0001
2705200	Messias	27.39	.0001
2704708	Marechal Deodoro	26.03	.0001
2706901	Pilar	25.94	.0001
2704302	Maceió	24.00	.0001
2708907	Satuba	23.76	.0001
2930709	Simões Filho	20.56	.0001
2919207	Lauro de Freitas	19.86	.0001

FIGURE 6

LISA CLUSTER MAP OF HOMICIDES, BLACK AND BROWN



THEORY AND WORKING HYPOTHESES

What factors help explain the variation and clustering observed above? Are there attributes of municipalities that explain most of this variation? Are there regional or contextual factors across sets or groups of municipalities? Does violence in one area spread or diffuse to other areas? Further, are the effects of explanatory factors—including diffusion—uniform across all geographic areas, or do they vary in meaningful and identifiable ways? Existing research highlights several explanations regarding the sources of violence—social disorganization, education, economic activity, and state capacity. We address these below and aggregate several indicators of social disorganization into a composite measure we call "marginalization." Moreover, building on the nonrandom clustering patterns identified in the previous section, expectations that are explicitly spatial in nature lead us to anticipate that regional factors shape patterns of violence, that violence in one area shapes patterns of violence in nearby areas, and that the effect of predictors of violence—including the diffusion effect—may be uneven across territorial units.

Research in sociology and criminology on the role of community context (Sampson and Groves 1989; Bursik Jr. and Grasmick 1999), "collective efficacy" (Sampson, Raudenbush, and Earls 1997), and social context (Thompson and Gartner 2014) in explaining crime and violence provide a central theoretical framework for explaining variation in homicide rates. According to Sampson and Groves (1989)—and following earlier research by Shaw and McKay (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's (2011) review of existing research found that higher rates of poverty have consistently been linked to higher rates of homicide in the United States and abroad. Other contributing factors include family disruption, which "may decrease informal social control at the community level" (Sampson 1986, cited in Sampson and Groves 1989, 781), and urbanization, which "weaken[s] local kinship and friendship networks and impede[s] social participation" (Sampson 1986, cited in Sampson and Groves 1989, 782). Thus, for Sampson and Groves (1989), community capacity to remain organized, i.e., to resist disorganization and therefore reduce crime, is shaped by macro-social and macro-economic factors such as resource deprivation, residential instability, ethnic heterogeneity, family disruption, and urbanization.[4]

Along similar lines, Land, McCall, and Cohen (1990) established three principal components from the primary predictors of interest. These three composite measures captured (1) population pressures, (2) resource deprivation/affluence, and (3) family disruption (see also Baller et al. 2001). Population pressures include total population and population density or concentration (i.e., urbanization is expected to lead to higher criminality), but they can also extend to other demographic pressures such as 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 (Land, McCall, and Cohen 1990; Baller et al. 2001) but could also be captured by indicators of single-parent households facing economic and child-care difficulties, as is the case with households headed by women who both work and have kids.

Education is widely regarded as having a protective effect against violence (Gottfredson 1985; Farrington et al. 1986; Ruhm 2000, 624), especially against homicide (Lochner and Moretti 2004; Ingram 2014; Ingram and Curtis 2014). Indeed, Mexico's former top anti-drug prosecutor identified the harmful consequences of the lack of education, noting the low education of many organized crime "foot soldiers" (Gonzalez 2013). Education exerts this protective effect in both direct and indirect ways. A direct effect occurs when more individuals, especially young men, are in school, so they are not elsewhere, e.g., spending time on the street, and consequently they are less likely to be either victims or perpetrators. That is, higher levels of educational enrollment and attainment mean that children stay in school longer 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 the 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

[4] 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.

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, to have a cultural, ideational, and ethical aversion to crime that is more reinforced than in people who did not spend time in school and perhaps engaged in other, even if petty, types of crime at an earlier age. Lastly, education allows citizens to communicate more effectively with each other, to learn each others' languages, and to strengthen community ties to improve their 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.

Some policies can also be expected to exacerbate or ameliorate social disorganization and opportunities for education. Bolsa Família (BF), a conditional cash transfer program, has the potential to soften or reverse disorganization. BF is widely regard as a holistic poverty-reduction program in which cash transfers hinge on, among other things, children's participation in school and family participation in health programs. Recent evidence from nonspatial research indicates that participation in BF decreases the incidence of homicide (Lance 2014), and that BF increases a sense of belonging and efficacy (Hunter and Sugiyama 2014), resonating with the sociological literature on the violence-reduction effects of collective efficacy, social capital, and community resilience (Ingram 2014).

Civic engagement contrasts with social disorganization, so any indicator of engagement or social capital should be negatively associated with violence. According to the social capital literature in political science (e.g., Putnam, Leonardi, and Nanetti 1994) and also sociology and demography (Sampson, Raudenbush, and Earls 1997; Yang, Noah, and Shoff 2013), civic participation or engagement should exert a downward pressure on violence. All else being equal, we anticipate that patterns of more intense civic engagement generate the social resources to reduce or even prevent criminal violence. Further, we expect that when civil society has a closer working relationship or partnership with government, homicide rates will be lower. That is, close public-private partnerships should make civil society more effective. Empirically, we expect civic engagement and public-private partnerships to have a negative relationship with violence. Environmental degradation can also contribute to social disorganization. Some development projects have more of an environmental impact (EI) than others. Projects with large environmental footprints—e.g., hydroelectric dams in the Amazon region—have this sort of footprint, generating grievances due to environmental concerns as well as to the displacement of large numbers of people. These projects also generate an influx of temporary workers and other transient populations with few or no ties to local communities.

Building on Land, McCall, and Cohen (1990), and following the above expectations regarding social disorganization and education, we anticipate the following predictors to have a positive relationship with homicide rates: population size, population density, proportion of the population that is rural, proportion of the population that is young and male, poverty, inequality, and environmental impact. In contrast, we anticipate that high levels of educational attainment and participation in Bolsa Família will have a negative relationship with homicide rates. Notably, several of these predictors capture similar phenomena and are correlated. Indeed, poverty rates, education, the proportion of the population that is eligible for Bolsa Família, and distance from the state capital are all highly correlated. Based on these initial explorations of our data, we constructed a principal component from these four variables and call this composite measure “marginalization.” In effect, marginalization captures elements of alienation or distance from material resources, schools and information, and public services. Thus, we expect that marginalization 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 (UNODC 2013, 7). We return to the issue of law enforcement presence below, but for now we 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. Beyond the conditions 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 underemployment creates financial stress and, therefore, incentives for 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 (2009) argues the anomic strain created by unemployment and a poorer economic system, along with poverty, increases homicide indirectly through property crime (see also Ingram and Curtis 2014).

In the United States, 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. Land, McCall, and Cohen (1990) and Baller et al. (2001) find consistent evidence that the unemployment rate has a negative relationship with homicide rates, arguing that reduced economic activity decreases opportunities for crime (Baller et al. 2001, 573; Raphael and Winter-Ebmer 2001). This counterintuitive relationship has also been found in Mexico (Ingram 2014). An 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 (Raphael and Winter-Ebmer 2001).

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 their citizenry effectively (Patrick 2011). 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 to 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 (Levitt 2004). We measure state capacity here as a principal component of several indicators of public service provision, including garbage collection, sewerage, and utility provision. Thus, state capacity captures a basic level of public service infrastructure.

Finally, to these hypotheses we add explicitly spatial hypotheses derived from the literature on diffusion and uneven territorial effects. First, phenomena of diffusion, spread, transfer, or spillover are receiving increasing attention in the social sciences, especially regarding the diffusion of crime and violence (Baller et al. 2001; Deane et al. 2008; Ingram 2014; Ingram and Curtis 2014; Dube, Dube, and García-Ponce 2013; Vilalta 2014). That is, we expect an increase in violence in nearby communities to cause an increase in violence in one's home, focal community. Second, the literature on subnational politics frequently calls attention to the uneven shape or performance of institutions across a country's territorial units or jurisdictions (Snyder 2001; Beer 2003; Falleti 2010; Gibson 2013; Ingram 2012). Drawing on this literature—and on the general expectation that the regional diversity within Brazil likely influences the underlying phenomenon of interest—we anticipate that both the spillover effect and predictors of violence will have an uneven effect across units.

DATA AND METHODS

Municipal homicide rates across several types of homicide in 2011 constitute the dependent variable, and data were obtained from the Brazilian Ministry of Health's System of Mortality Information (Sistema de Informações sobre Mortalidade). We selected 2011 as the year in which to measure the outcomes of interest because of the proximity of this year to a large number of explanatory variables collected during the decennial year (2010). Across all models, we used the logged, spatially smoothed version of each outcome (see note 3). Given that the smoothed outcome eliminates some of the variation in the dependent variable, it can be harder to find significant results. Thus, the results reflect some of the more conservative estimates among auxiliary models.[5]

Explanatory variables for the spatial regressions are from 2009 or 2010. All the demographic data come from the United Nations Development Program's (UNDP) *Atlas of Human Development in Brazil* (*Atlas do Desenvolvimento Humano no Brasil 2013*), using data from the 2010 census. Finally, data from the Brazilian Institute of Geography and Statistics (Instituto Brasileiro de Geografia e Estatística, IBGE) provide the remaining explanatory

[5] Results of GWR-SL models with logged version of dependent variables are available from authors.

variables.[6] More specifically, population density captures total population divided by the area of the municipality (sq. km.). The proportion of the population that is young and male captures all males age eighteen to twenty-nine. All population figures were logged. The employment rate is for all adult males age eighteen or older, so can be more accurately understood as an adult male employment rate (AMER). Family disruption is captured by a measure of female-headed households in which the woman has no education, works, and has children under age fifteen (FHHWK). Marginalization is a principal component of poverty, literacy rates, and eligibility for Bolsa Família. State capacity is a principal component of public service provision, including the provision of electricity and water, sewerage, and garbage collection. Environmental impact (EI) is a dichotomous variable (0,1) that captures the presence of large-scale development projects with an environmental footprint. A Gini coefficient captures inequality. We capture the intensity of civic engagement with the density of civil society organizations (CSO density) by dividing the total number of CSOs by the municipal population; this measure is logged. Close partnerships with government are captured by a dichotomous variable (Council) that registers when nonprofits have a seat on the local development council.

Spatial analysis lends itself to the study of the diffusion phenomena and uneven causal relationship outlined in the theory section above. The key analytic benefit of spatial analysis is the dependent structure of the data, and several specifications of spatial regressions explicitly account for how the incidence of the outcome of interest in connected units affects the outcome of interest in a home, focal unit (e.g., spatial lag), and on how the magnitude, direction, or significance of predictors and the spatially lagged dependent variable can be uneven across units of analysis. We first specify basic spatial lag and spatial error models. Formally, the general spatial model can be expressed in matrix notation as follows (Anselin 1988):

$$\begin{aligned} y &= \varrho W y + X\beta + \varepsilon \\ \varepsilon &= \lambda W \varepsilon + \mu \end{aligned} \tag{1}$$

[6] The UNDP Atlas is available at http://atlasbrasil.org.br/2013/pt/download; IBGE data on nonprofits at http://www.ibge.gov.br/home/estatistica/economia/fasfil/2010/; and IBGE municipal data at http://www.ibge.gov.br/home/estatistica/economia/perfilmunic/2009/default.shtm (last accessed Nov. 24, 2014).

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.

$$y = X\beta + \varepsilon \tag{2}$$

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, based on our interest in the uneven effect of both the diffusion effect and the predictors of violence, we build a variant of geographically weighted regression (GWR: Fotheringham, Brunsdon, and Charlton 2003; Charlton, Fotheringham, and Brunsdon 2009). Specifically, we follow Shoff, Chen, and Yang (2014) in specifying a geographically weighted spatial lag regression (GWR-SL).

Geographically weighted regression (Brunsdon, Fotheringham, and Charlton 1996; Fotheringham, Brunsdon, and Charlton 2003;Charlton, Fotheringham, and Brunsdon 2009) estimates the local coefficient for predictors. As noted by the developers, GWR allows “different relationships to exist at different points in space” (Brunsdon, Fotheringham, and Charlton 1996, 281), thereby facilitating the analysis of spatial heterogeneity (Shoff, Chen, and Yang 2014, 558). To be clear, GWR is generally used to estimate the locally varying coefficients for predictors of interest, and therefore the focus is on spatial heterogeneity. In matrix notation, GWR can be expressed as:

$$y_i = \beta_i X_i + \varepsilon_i \tag{3}$$

Here, y_i is the outcome of interest at location i (identified by coordinates [u,v], where u is the x-coordinate at location i, and v is the y-coordinate at location i) , X_i is the set of predictors at location i, ε_i is a random error term, and β_i is a vector of local coefficients associated with the predictors in X.

Complementing GWR's strength in detecting spatial heterogeneity, Brunsdon, Fotheringham, and Charlton (1996, 296) originally suggested that their model could be extended to "generate localized spatial autocorrelation statistics from a GWR version of Ord's model." Similarly, Shoff, Chen, and Yang (2014) propose modifying the basic GWR model to simultaneously account for spatial homogeneity. In other words, by adding a spatial lag of the outcome of interest—which presumes at least some degree of spatial homogeneity, i.e., that the outcome in one place is related to the outcome in nearby places—Shoff, Chen, and Yang (2014) propose a GWR with a spatial lag, calling this GWR-SL. Following these authors, we first calculate the spatial lag of the outcome (Wy) at each location i, just as one might do for a spatial lag model (SLM), and then estimate a GWR model that includes Wy among the predictors.[7] Thus, the equation for GWR-SL can be expressed as:

$$y_i = \rho_i W_i y + \beta_i X_i + \varepsilon_i \tag{4}$$

In equation 4, ϱi captures spatial homogeneity as the locally varying lag effect of the outcome of interest, while βi captures spatial heterogeneity as the locally varying effect of predictors. To be sure, if ϱ exhibits broad variation across all units i, then there may be little spatial homogeneity. In either case, the GWR-SL model promises results that can help identify regions of the country where both ϱ and β may vary in statistical significance, direction, and magnitude. Location i is captured by the latitude and longitude of the centroid of each municipality, and estimating β is based on a weights matrix conditioned by other observations in the data set and therefore changes for each location, yielding local coefficients.

Two cautions are in order regarding the use of GWR. First, Wheeler and Tiefelsdorf (2005) caution against using GWR when the estimated coefficients are highly correlated.

[7] One risk of including Wy among the predictors is that the significance of other variables may be obscured, just as the inclusion of a temporal lag of the outcome (lagged dependent variable, LDV) can obscure significance (Achen 2001). An alternative might follow Shoff, Chen, and Yang (2014), who estimate a two-stage version of this kind of geographically weighted regression with a spatially lagged dependent variable (GWR-SL). Here, we do not employ a two-stage process.

Overall, this is not a concern for us, though we address it in the GWR-SL analysis of femicides below. Second, Páez, Farber, and Wheeler (2011) caution against using GWR with small sample sizes. They recommend samples larger than 1,000, and caution against samples smaller than 160. Our sample of 5,562 clears this hurdle.

SPATIAL REGRESSIONS

Complementing the descriptive data and exploratory analysis above, this section develops a fuller, more explanatory analysis. Spatial regressions proceed in two stages. First, Tables 6–10 report results from the basic ordinary least-squares (OLS), SEM (spatial error model), and SLM specifications. Second, diagnostics of the OLS models identify which variables have non-stationary effects (Table 11). Based on these diagnostics, Figures 7–12 visualize the results of the GWR-SL models by mapping the locally varying coefficients. Taken together, the findings from all regressions identify the strongest predictors, how the significance, magnitude, and direction of predictor effects vary across municipalities, whether homicide diffuses from nearby communities to focal communities, and how the significance, magnitude, and direction of this diffusion effect also vary across municipalities. Furthermore, the findings identify all of these effects across five types of homicide, contributing a nuanced and disaggregated examination of the sources of violence, providing support for some existing policies and helping support the development of additional policies to reduce or prevent violence.

The tables examine the overall homicide rate (Table 6), the homicide rate for men only (not reported, since they closely track results for all homicides), the homicide rate for women only ("femicides," Table 7), gun-related homicides (Table 8), the homicide rate for youth only (Table 9), and the homicide rate for victims identified as black or brown, i.e., nonwhite (Table 10). Three models examine variation of each measure—OLS, SEM, and SLM.

In conventional spatial analysis, Lagrange Multiplier (LM) tests also identify whether to pursue an error or lag specification. Here, LM tests suggest that the models of three dependent variables—all homicides, homicides of men, and homicides of black and brown victims—follow mixed SEM and SLM pattern (basic and robust LM tests significant for both error and lag processes), but all other types of homicides examined here (femicides, gun-related homicides, and homicides of youth) follow a spatial lag process (basic LM tests significant for both error and lag processes, but robust tests only significant for lag process; test results not reported here).

This suggests that an SLM may be most appropriate for femicides, gun-related homicides, and youth homicides. Future research may also be needed to explore a mixed, spatial Durbin model of the other types of homicides (aggregate, men only, and black and brown victims), but such a mixed model is beyond the scope of this paper. Thus, policymakers should be more attuned to diffusion processes for these types of violence. Further, rho has a larger magnitude for firearm and youth homicides than for femicides, so the diffusion effect is stronger with these two types of violence.[8]

The findings from Table 6 (all homicides) fall into three categories. First, highlights from Table 6 include the most robust findings, i.e., those that have consistent statistical significance and direction of effect across all models: (1) marginalization is statistically significant across all models and always in the anticipated positive direction; (2) the proportion of households headed by women who also work has a consistently significant and positive relationship with homicide rates; (3) the employment rate for men above the age of eighteen has a consistently significant and unexpectedly positive relationship with homicide rates; (4) state capacity has a consistently significant and unexpectedly positive relationship with homicide rates; (5) the spatial error term (lamda) is significant and positive in both SEM specifications, suggesting greater attention to unmeasured covariates; and (6) and the spatial lag term (rho) is statistically significant in both SLM specifications and exerts a positive effect, indicating that homicides in one municipality can be explained by homicides in neighboring municipalities.

Third, Table 6 includes mixed evidence regarding population, which exerts a statistically significant positive effect in the first set of models but a statistically significant negative effect in the second set of models.

Turning to homicides of men only (results not reported here), many of the same results remain. This is perhaps unsurprising since most homicide victims are male. Highlights once

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[8] Substantial residual spatial autocorrelation remains after estimating the basic OLS regression across all models (large LM, $p<0.05$), indicating that spatial regressions are in order. Notably, across all spatial regressions, the degree of spatial autocorrelation is greatly diminished, if not eliminated. Spatial autocorrelation remains an issue in the second set of models in each table, which examine the smoothed version of the dependent variable.

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 all tables. 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. The continued presence of spatial autocorrelation in some of the spatial models again suggests the need for attention to omitted variables.

again include the consistently significant and positive effect of marginalization, female-headed households, adult male employment rate, state capacity, spatial error term (lamda), and the spatial lag term (rho). Among the other provocative findings, BF coverage exerts the same significant and negative effect on homicide rates, and EI exerts the same significant and positive effect. Notably, the SEM appears to be a better model, at least for the second measure (lhrebmen), as evidenced by the rise of the Akaike Information Criterion (AIC) from SEM to SLM. Interpreted alongside the LM tests earlier, which suggested that homicides of men and of blacks and browns follow error structure, not lag structure, the results from the SEM should be privileged.

TABLE 6

SPATIAL REGRESSIONS FOR ALL HOMICIDES

	Y=lhreb		
	OLS	SEM	SLM
Variable	Est.	Est.	Est
(Intercept)	-9.391***	-8.891***	-4.776***
Population	-0.027**	-0.040***	-0.032***
Rural	-0.054***	-0.040***	-0.043***
Density	0.006	0.008	0.002
Young males	-0.285***	-0.230**	-0.213**
GINI	0.116	-0.020	-0.007
Marginalization	0.236***	0.152***	0.156***
FHHWK	0.004***	0.003**	0.003***
AMER	0.007***	0.005***	0.005***
CSO density	0.013ŧ	0.017**	0.013*
Council	0.060**	0.033ŧ	0.035ŧ
BF coverage	-0.001***	-0.001**	-0.001**
EI	0.101***	0.057***	0.070***
State capacity	0.137***	0.102***	0.090***
Lamda		0.507***	
Rho			0.492***
N	5,562	5,562	5,562
AIC	7843.1	6930.4	6896.2
Wald		1145.3	1167.5
LR		-3449.21	-3432.11
LM	1300.37	15.96	18.14
Pr(LM)	<.001	<.001	<.001

*** p<.001, ** p<.01, * p<.05, ŧ p<.10

TABLE 7

SPATIAL REGRESSIONS FOR HOMICIDES OF WOMEN ONLY (FEMICIDES)

	Y=lhrebfem		
	OLS	SEM	SLM
Variable	Est.	Est.	Est
(Intercept)	-10.030***	-10.024***	-7.081***
Population	0.001	0.002*	0.001Ŧ
Rural	-0.002***	-0.004***	-0.003***
Density	-0.001Ŧ	-0.001Ŧ	-0.001
Young males	-0.003	-0.003	-0.004
GINI	0.022	0.014	0.015
Marginalization	0.009***	0.007***	0.007***
FHHWK	0.000	0.000	0.000
AMER	0.000***	0.000**	0.000***
CSO density	0.000	0.001	0.001
Council	0.004Ŧ	0.003	0.003
BF coverage	0.000	0.000	0.000
EI	0.006***	0.005**	0.005**
State capacity	0.007***	0.004***	0.005***
Lamda		0.299***	
Rho			0.295***
N	5,562	5,562	5,562
AIC	-18108	-18454	-18453
Wald		376.47	377.39
LR		9242.986	9242.675
LM	621.85	5.75	5.11
Pr(LM)	<.001	0.02	0.02

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

The analysis of femicides reveals the first major departure from earlier results. While marginalization and the percent of men who are employed maintain the same relationship with homicides of women, FHHWK and BF coverage are no longer significant. The starkest change, however, relates to environmental impact (EI). Across all models, environmental impact had a strong and positive relationship with femicides.[9] Population pressures stabilize and have a more consistent relationship with outcome. Areas with large populations, but not densely populated and not rural, seem to be dangerous for women.

Turning to gun-related homicides, the result regarding marginalization remains, but the two results that merit more attention are the strong dampening (negative) effect of BF coverage and the positive effect of EI. That is, the degree of participation in BF reduces gun-related homicides, while EI increases these homicides. Indeed, BF coverage has the most pronounced effect here, and in the anticipated direction. Specifically, Bolsa Família coverage has a negative and statistically significant relationship with gun-related homicides in all models. Thus, while it may not help reduce the incidence of all homicides, BF reduces the incidence of firearm-related homicides.

For youth homicides, the results regarding marginalization and FHHWK remain. Also, BF coverage exerts the same, consistently dampening effect on youth homicides as was seen with gun-related homicides.

[9] Both SEM and SLM improve on OLS, but with no real difference in model fit between SEM and SLM. Still, based on RLMerr and RLMlag tests, we should pay more attention to SLM results.

TABLE 8

SPATIAL REGRESSIONS FOR GUN-RELATED HOMICIDES

	Y=lhrebgun		
	OLS	SEM	SLM
Variable	Est.	Est.	Est
(Intercept)	-9.713***	-8.915***	-4.678***
Population	-0.088***	-0.106***	-0.088***
Rural	-0.059***	-0.042***	-0.052***
Density	0.047***	0.044***	0.026***
Young males	-0.459***	-0.290**	-0.282***
GINI	-0.097	-0.161	-0.168
Marginalization	0.295***	0.178***	0.189***
FHHWK	0.003**	0.002[Ŧ]	0.002*
AMER	0.008***	0.005***	0.006***
CSO density	0.015[Ŧ]	0.014[Ŧ]	0.009
Council	0.072**	0.027	0.035[Ŧ]
BF coverage	-0.002***	-0.002***	-0.001***
EI	0.129***	0.075***	0.093***
State capacity	0.131***	0.095***	0.081***
Lamda		0.511***	
Rho			0.491***
N	5,562	5,562	5,562
AIC	9630.8	8668.5	8658.8
Wald		1213	1195.5
LR		-4318.27	-4313.42
LM	1404.27	19.07	16.56
Pr(LM)	<.001	0.03	0.99

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

TABLE 9

SPATIAL REGRESSIONS FOR HOMICIDES OF YOUTH ONLY

	Y=lhrebyth		
	OLS	SEM	SLM
Variable	Est.	Est.	Est
(Intercept)	-8.436***	-7.948***	-4.599***
Population	-0.081***	-0.088***	-0.076***
Rural	-0.061***	-0.049***	-0.054***
Density	0.019**	0.020*	0.011ŧ
Young males	-0.462***	-0.393***	-0.349***
GINI	-0.033	-0.152	-0.132
Marginalization	0.204***	0.140***	0.147***
FHHWK	0.002*	0.001	0.001*
AMER	0.006***	0.003***	0.004***
CSO density	0.012ŧ	0.017**	0.011ŧ
Council	0.069***	0.048**	0.049**
BF coverage	-0.001***	-0.001***	-0.001**
EI	0.093***	0.057***	0.069***
State capacity	0.100***	0.079***	0.066***
Lamda		0.458***	
Rho			0.440***
N	5,562	5,562	5,562
AIC	7228	6510.2	6510.4
Wald		847.49	849.92
LR		-3239.09	-3239.20
LM	1032.72	11.96	9.01
Pr(LM)	<.001	<.001	0.003

*** p<.001, ** p<.01, * p<.05, ŧ p<.10

TABLE 10

SPATIAL REGRESSIONS FOR HOMICIDES OF NONWHITE VICTIMS ONLY

	Y=lhrebbkbn		
	OLS	SEM	SLM
Variable	Est.	Est.	Est
(Intercept)	-8.827***	-8.328***	-4.345***
Population	-0.077***	-0.083***	-0.068***
Rural	-0.020**	-0.022**	-0.025***
Density	0.033***	0.023**	0.017**
Young males	-0.387***	-0.294***	-0.246***
GINI	0.137	0.080	0.069
Marginalization	0.142***	0.072***	0.097***
FHHWK	0.002**	0.001	0.002*
AMER	0.008***	0.005***	0.005***
CSO density	0.011[Ŧ]	0.013*	0.010[Ŧ]
Council	0.071***	0.044**	0.048**
BF coverage	-0.002***	-0.001***	-0.001***
EI	0.065***	0.038**	0.047**
State capacity	0.114***	0.097***	0.074***
Lamda		0.514***	
Rho			0.492***
N	5,562	5,562	5,562
AIC	6941.9	5935.6	5960.7
Wald		1266.3	1209.5
LR		-2951.79	-2964.33
LM	1523.77	19.24	12.36
Pr(LM)	<.001	<.001	<0.001

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

For victims classified by race as black or brown (i.e., nonwhite), the results regarding marginalization, FHHWK, and AMER remain. Also, BF coverage is consistently significant and in the anticipated negative direction. EI is also significant in all models and always exerts a positive effect on the outcome of interest. Conditional cash transfer programs help reduce violence experienced by black and brown individuals, and the harmful effects of environmental impacts are felt more consistently by black and brown individuals.

UNPACKING KEY FINDINGS: GWR-SL

The coefficient for the spatial lag of the outcome is positive and statistically significant across all models above, suggesting that for all types of homicide, homicide in nearby municipalities increases the risk of homicide in one's home municipality. However, this coefficient is a single value reporting the average effect of the spatial lag (rho) for all municipalities. This is not very satisfying, as it is unlikely that a rise in homicides in one part of the country (e.g., south) would have exactly the same effect as a rise in another part of the country (e.g., northeast). It would be more analytically satisfying, and also more useful for targeting policy, to estimate a local value for rho, thus identifying how the effect of nearby homicides varies throughout Brazil. Similarly, it would be beneficial to estimate locally varying effects of other predictors. Thus, with the evidence of the previous analyses in mind, this section generates a finer understanding of the main results by (a) identifying which of the coefficients above have a uniform effect across all municipalities (i.e., global effect), and (b) identifying which coefficients vary in magnitude, direction, or significance across municipalities (i.e., local effect) and estimating that local effect. Among the more intriguing estimates is the locally varying coefficient for violence in nearby municipalities (rho), as this would give a refined understanding of the diffusion of violence.

Table 11 and Figures 7–111 report the results of the GWR-SL analysis. Table 11 begins by reporting Monte Carlo tests for stationarity.[10]

[10] All tests executed in R using packages "GWmodel", v.1.2-3 (Lu et al. 2015).

TABLE 11

MONTE CARLO TEST FOR STATIONARY

	All homicides	Femicides	Firearms	Youth	Nonwhite
(Intercept)	0.020	0.010	0.000	0.000	0.010
Population	0.000	0.000	0.000	0.000	0.000
Rural	0.000	0.000	0.000	0.000	0.000
Density	0.000	0.020	0.000	0.000	0.000
Young males	0.000	0.020	0.000	0.000	0.000
GINI	0.000	0.000	0.000	0.010	0.020
Marginalization	0.000	0.000	0.000	0.000	0.000
FHHWK	0.050	0.069	0.317	0.119	0.109
AMER	0.465	0.079	0.188	0.475	0.050
CSO density	0.010	0.010	0.000	0.000	0.020
Council	0.089	0.248	0.050	0.366	0.109
BF coverage	0.000	0.000	0.000	0.000	0.000
EI	0.158	0.653	0.248	0.129	0.059
State capacity	0.000	0.000	0.000	0.000	0.000
Spatial lag (rho)	0.000	0.010	0.000	0.000	0.000

Nsims=99; no major changes with nsims = 1000 for all, but computation time extended.

In sum, rho is always non-stationary, along with marginalization, GINI, state capacity, BF coverage, and CSO density. Conversely, EI and Council are always stationary and aside, from a nearly significant result in a single category, FHHWK and AMER are also always stationary. Other predictors vary in their stationarity across types of homicide.

Based on these diagnostics, we estimate locally varying coefficients for all non-stationary predictors. To economize space, we exclude all population variables as policy implications related more directly to other predictors of interest (full results available from authors). Following Wheeler and Tiefelsdorf (2005) we also examine collinearity among coefficients (pair plots available from authors). We did not detect serious multicollinearity except in the model of femicides, where the coefficient for the SL of the DV (rho) was collinear with intercept. Thus, we exercise more caution in interpreting the GWR-SL results of that model and do not map those results.

Maps of the locally varying coefficients help understand the results (Matthews and Yang 2012).[11] Figures 7–12 visualize the uneven effect of non-stationary coefficients, organizing the results by predictor to ease assessment of the underlying theory. We discuss each of the figures below following a similar structure, highlighting the significance, direction, magnitude, variation across types of homicide, and special geographic regions of concern.

Figure 7 reports the results for rho (spatial lag), showing how the strength of diffusion of the outcome of interest varies across space. The coefficient is statistically significant throughout nearly the entire country, with only a small area in the south-central part of Brazil where violence in nearby areas does not appear to affect violence in one's home community. The absence of a diffusion effect in this small area is intriguing and a potential avenue of future research. The direction of the diffusion effect is also notable because it is always positive. That is, violence in nearby communities always increases violence in one's home community, i.e., *regional violence always increases local violence*. Further, this is true across all types of homicide. Strongest regions of diffusion include the Amazon and the central part of the eastern coast, spanning from Espírito Santo north. Notably, there are large areas of strong diffusion that cross or straddle state boundaries, drawing attention to issues of cross-jurisdictional policy coordination.

Figure 8 reports the results for inequality (GINI). Inequality's significance varies widely but is consistently significant across the northern part of the country and in sections of the south. The variation in direction appears to be driven primarily by the variation in direction for gun-related and youth homicides, since there is much less variation in direction for nonwhite

[11] For all homicides, bandwidth was 676; AICc (small sample bias corrected AIC, see GWR manual, 26) of local regression (6052.8) is substantially lower than that of global regression (6513.6), supporting the choice of GWR model over OLS; ANOVA comparison of OLS and GWR (Brunsdon et al. 1999, 507–11) shows that GWR is preferable to OLS (F = 2.77; p<0.01); AIC of GWR-SL model is also much lower than AIC of either SEM or SLM, suggesting this is the best model. For femicides, bandwidth was 506; AICc of local regression (-19660.1) is substantially lower than that of global regression (-18572.9), again supporting the choice of GWR model. For gun-related homicides, bandwidth is 549; AICc of local regression (7717.02) is substantially lower than that of global regression (8283.60). For youth homicides, bandwidth is 653; AICc of OLS = 6210.2; AICc of GWR = 5611.77; ANOVA: F=3.10; p<0.001. Finally, for nonwhite homicides, bandwidth is 651; OLS AICc = 5584.42; GWR AICc = 4983.66.

homicides. Specifically, inequality has a positive relationship with nonwhite homicides across most of the northern part of Brazil, especially across the northern part of the Amazon region along the borders with the Guianas, Venezuela, and Colombia. The positive relationship is particularly widespread and strong for nonwhite homicides; that is, inequality appears to increase the risk of nonwhite homicide in the north of Brazil. This positive local relationship fits with theoretical expectations but cuts against the negative relationship in the south and in the global model.

Figure 9 reports results for marginalization. Marginalization has a non-stationary effect on all homicides, varying in magnitude, significance, and direction, as well. Marginalization has an expected positive relationship on homicides in four main regions of the country: the Amazon (overlapping Pará and Amazonas), the central region (overlapping Mato Grosso, Mato Grosso do Sul, and Goiás), a coastal region (spanning from northern Santa Catarina up to southern Bahia), and a smaller region near the borders of Bahia, Piauí, and Tocantins. The Amazon effect is driven primarily by youth and nonwhite homicides; the central effect is driven primarily by firearm violence; and the coastal effect and smaller region in the northeast are a combination of firearm, youth, and nonwhite homicides. Maranhão is the only state where a theoretically unexpected negative relationship between marginalization and homicide appears, and this relationship holds for firearm, youth, and nonwhite homicides.

Figure 10 reports results for CSO density. Significance varies widely, with large sections of the country showing no statistical relationship between CSO density and any type of homicide. Moreover, where significance holds—in the Amazon and in smaller pockets elsewhere—the direction of the effect varies. Unexpectedly, the effect is positive in some areas (e.g., Amazon) but in the expected negative direction elsewhere (e.g., parts of Maranhão).

Figure 11 reports results for BF coverage. This effect is only significant in certain areas, though it is consistently significant across all types of homicide in the northeast of Brazil. The direction is always negative, showing how participation in this program decreases violence. The magnitude of the effect also varies, though again the strongest effect appears in the northeast, covering parts of Maranhão, Piauí, and Bahia.

Figure 12 reports results for state capacity. The significance of the effect varies widely, but the effect is consistently significant across the Amazon basin and in the south of the country. Interestingly, the direction of the effect is inverted in these two areas: state capacity has a positive effect on homicide (across all types) in the Amazon, but has a negative effect on violence in small pockets in the south of the country. As noted above, this finding was unexpected. The most likely explanation is some kind of endogeneity, in that an increase in violence is likely to trigger an increased response from the state.[12] Future research may also be able to disentangle this relationship with longitudinal data.

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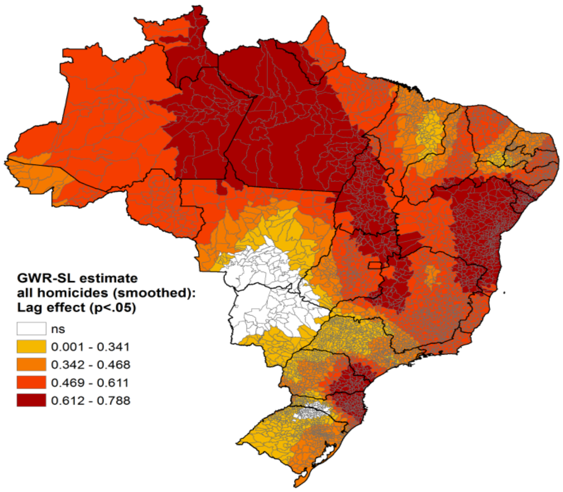
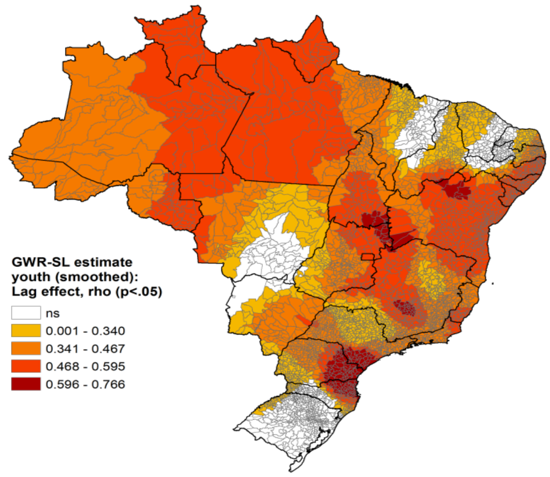
[12] Findings regarding state capacity and employment rates, though counterintuitive, align with recent research in the United States. Regarding state capacity, existing research suggests the finding here may be endogenous; that is, the positive association is a result of state resources being directed at areas of high violence, rather than state capacity causing an increase in violence. Additional research would be needed to examine this endogeneity. Regarding employment rates, higher employment rates create more targets for crime and violence; thus we should expect to see homicide and other crime rates increase as economic activity increases.

FIGURE 7

GWR-SL RESULTS FOR LAG EFFECT (RHO)





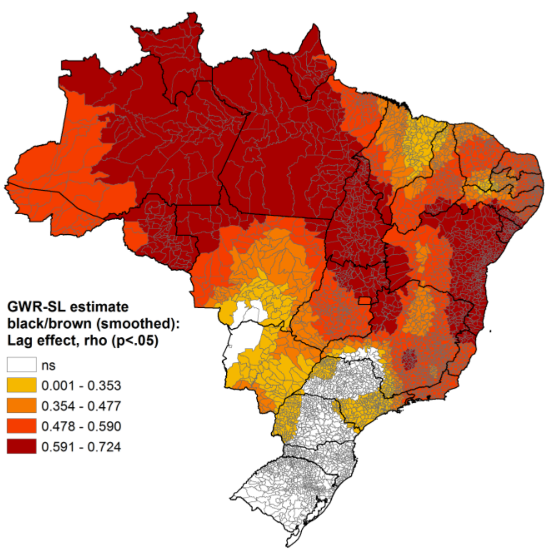


FIGURE 8

GWR-SL RESULTS FOR GINI

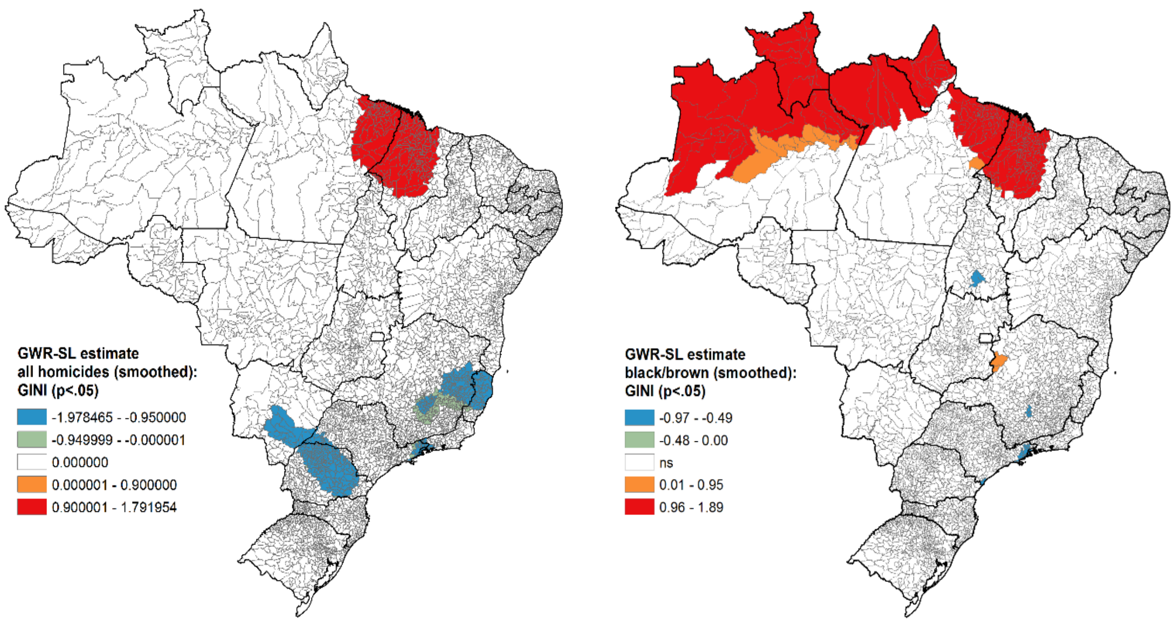


FIGURE 9

GWR-SL RESULTS FOR MARGINALIZATION

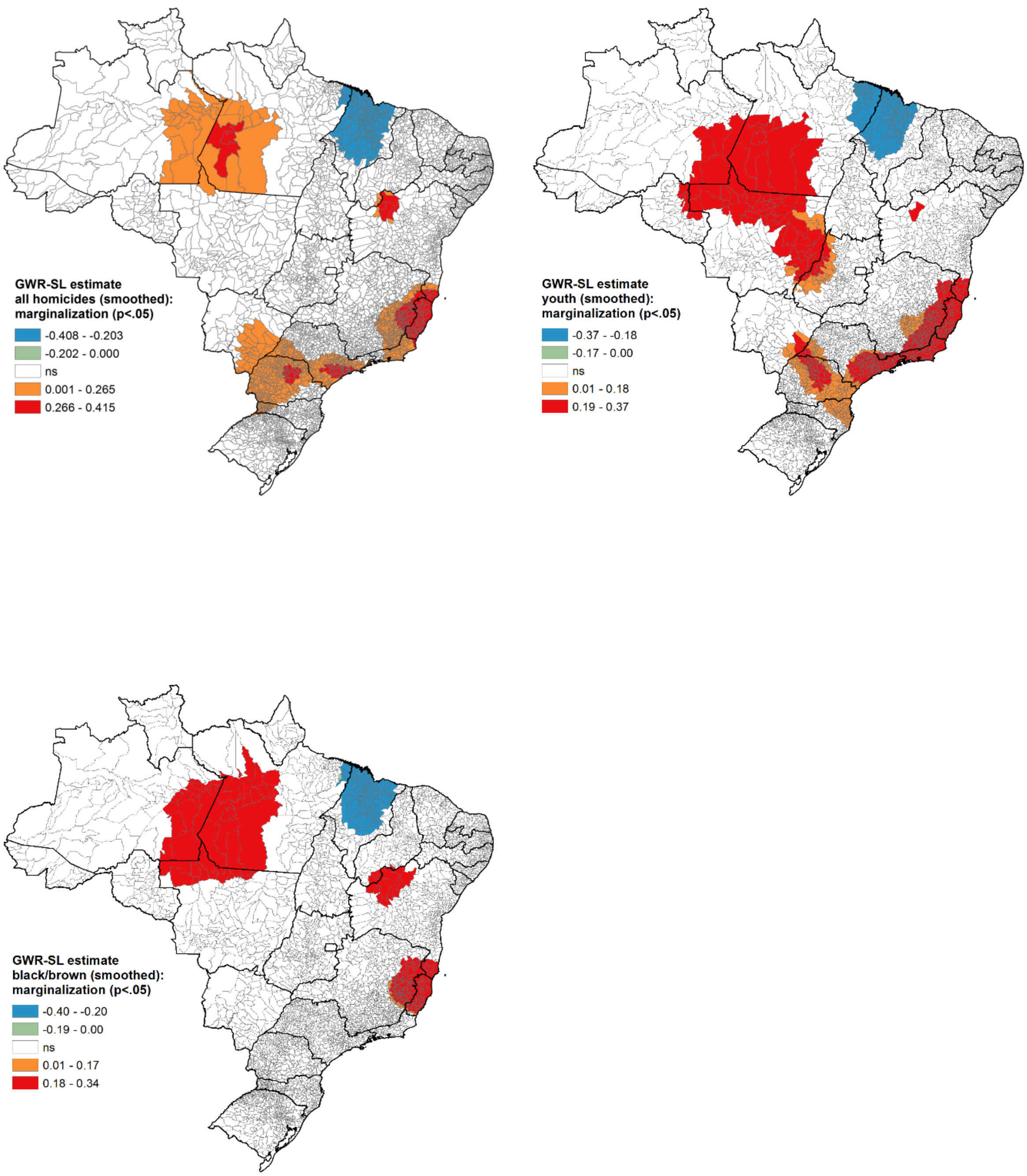


FIGURE 10

GWR-SL RESULTS FOR CSO DENSITY

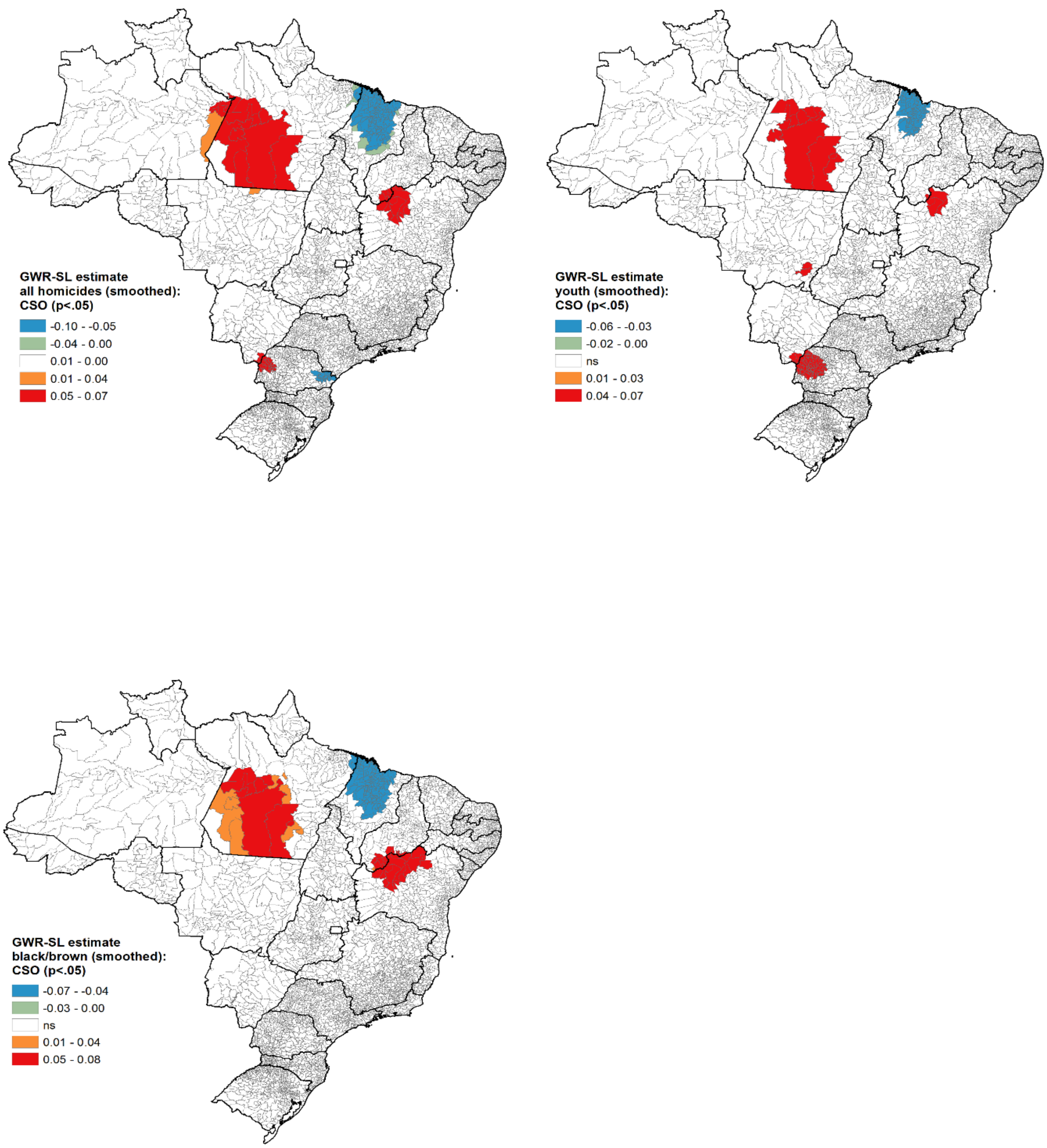


FIGURE 11

GWR-SL RESULTS FOR BF COVERAGE

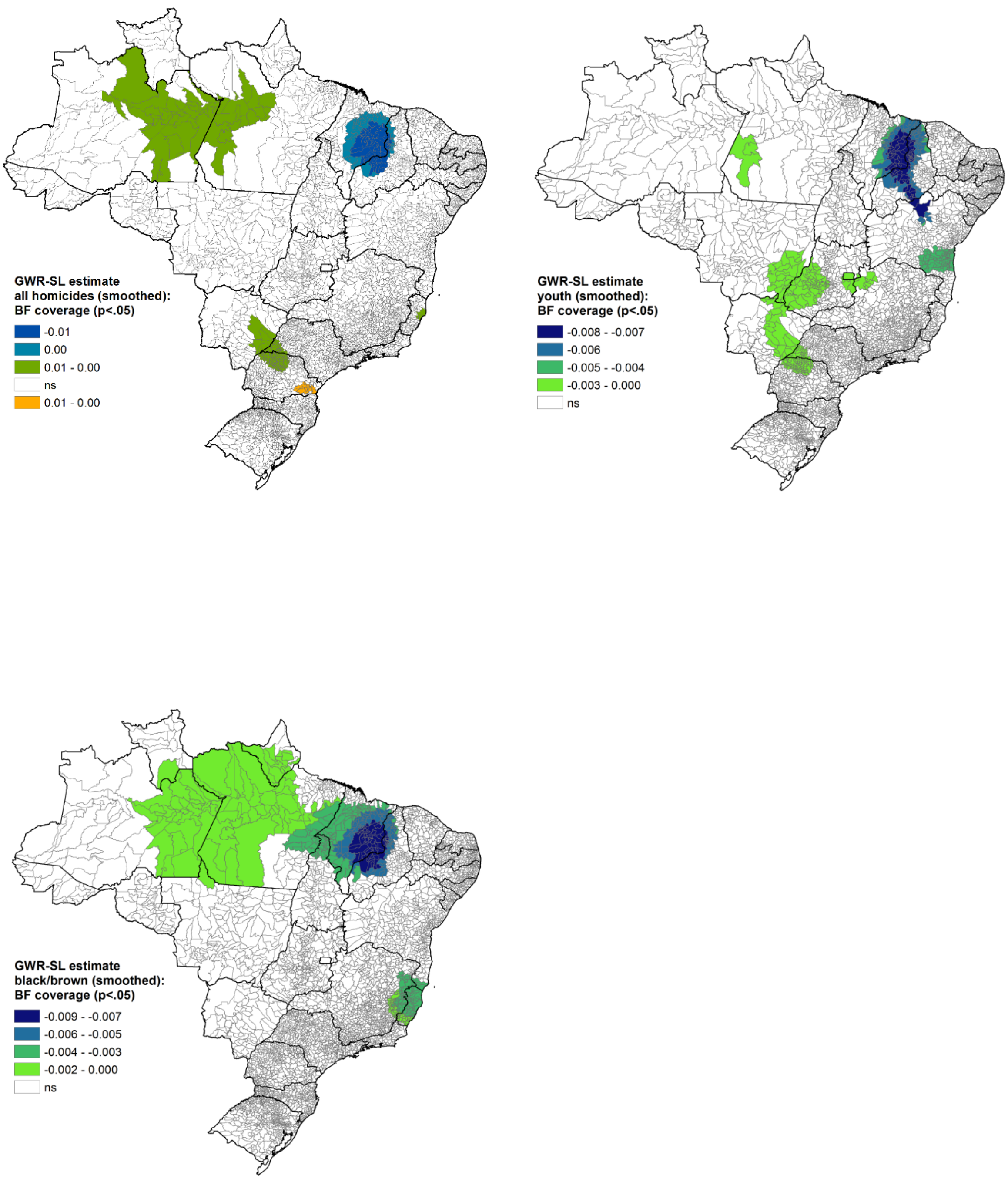
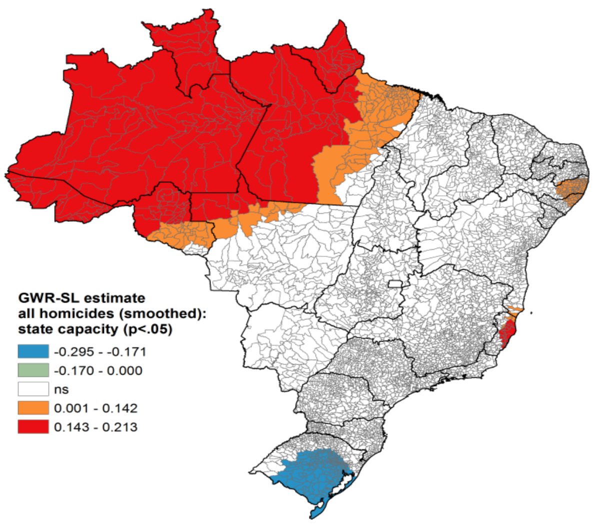
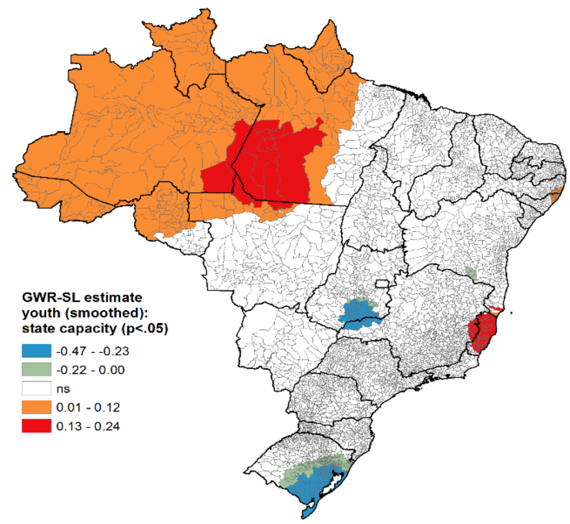
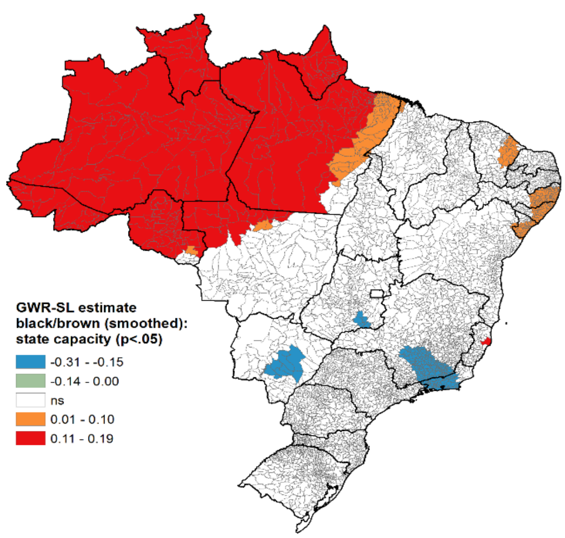


FIGURE 12

GWR-SL RESULTS FOR STATE CAPACITY







CONCLUSIONS AND IMPLICATIONS

This study presents a spatial analysis of violence across Brazil's 5,562 municipalities. More specifically, the paper builds towards a geographically weighted regression of five types of homicide: all homicides, femicides, gun-related homicides, youth homicides, and nonwhite homicides. Taken together, the findings from all regressions identify the strongest predictors of homicide; how the significance, magnitude, and direction of predictor effects vary across municipalities; whether homicide diffuses from nearby communities to focal communities; and how the significance, magnitude, and direction of this diffusion effect also vary across municipalities. Furthermore, the findings identify all of these effects across five types of homicide, contributing a nuanced and disaggregated examination of the sources of violence, providing support for some existing policies and furthering the development of additional policies to reduce or prevent violence.

Core results show that some predictors have stationary (i.e., uniform or stable) effects across all units (Council, EI, AMER, FHHWK), while other predictors have uneven, non-stationary effects (GINI, CSO density, marginalization, BF coverage, state capacity, and the spatial lag term, rho). Among the stationary effects, key findings include:

(1) Family disruption and social disorganization, captured by the percentage of females with no education who are heads of households and have kids under age fifteen, has a harmful effect across all types of homicide except femicides.
(2) Economic activity, captured by the adult male employment rate (AMER), has a consistently significant and unexpectedly positive relationship with all types of homicide, though the effect is less consistent with homicides of black and brown victims. The direction of this effect aligns with research in the United States (Land, McCall, and Cohen 1990; Baller et al. 2001), Mexico (Ingram 2014), and Central America (Ingram and Curtis 2014), suggesting that increases in economic activity generate more targets and opportunities for criminal violence.
(3) Environmental degradation (EI) has a harmful effect on women; there is a strong, positive association between EI and the femicide rate, but EI is also consistently harmful for gun-related, youth, and nonwhite homicides.

Among non-stationary, locally varying effects, the main findings include the following:

(4) Marginalization—a composite measure including indicators of poverty, illiteracy, and rurality—has a harmful effect across all measures of homicide and across all models; put briefly, as marginalization increases, homicide rates increase. That said, marginalization poses the greatest danger to nonwhite populations in the northern part of Brazil. In small geographic pockets, marginalization has a negative influence on homicide.

(5) The proportion of poor, eligible families covered by Bolsa Família (BF coverage) has a protective, negative effect for most types of homicides, but the findings are most consistent for gun-related, youth, and nonwhite homicides. These findings suggest that conditional cash transfer programs are a promising policy option in the struggle to prevent and reduce violence, especially in the struggle to prevent or reduce firearm-related violence and violence directed at youth and nonwhite populations.

Among explicitly spatial results, key findings include:

(6) Different types of homicide cluster geographically in nonrandom and identifiable ways.

(7) Homicide in nearby communities increases the likelihood of homicide in one's home, focal community. And

(8) The effect of homicide in nearby areas—the diffusion effect—also varies across geographic areas, i.e., it is non-stationary. Specifically, the danger posed by nearby violence is strongest in the Amazon region and in a large section of the eastern coast, from Espírito Santo to the northeastern states of Sergipe and Alagoas.

Policy implications that derive from these conclusions fall into three main areas: (1) substantive content of violence-reduction and violence-prevention policies; (2) how to prioritize these policies; and (3) targeting of violence-reduction or violence-prevention policies according to both type of homicide and geographic area.

First, the findings strongly support policies that (a) reduce marginalization, (b) reduce family disruption by reducing the incidence of females with no education who are heads of households and have children, (c) reduce the environmental impact of industrial development projects, and (d) increase coverage of conditional cash transfer programs such as Bolsa Família.

One of the main findings relates to the utility of conditional cash transfer programs in reducing gun-related homicides, youth homicides, and homicides of nonwhite victims, but its lack of any effect with regards to other types of homicides. These cash transfer programs, then, have a valuable violence-prevention power. To be clear, the mechanism by which this happens is not elucidated here. It may be that these programs reduce marginalization (which we find contributes to all types of homicides across the board) and therefore indirectly reduce violence. The causal pathway remains an open question, but the results here regarding BF coverage and several types of homicide have clear policy implications. Specifically, conditional cash transfer programs are a promising policy option in the struggle to prevent and reduce violence, especially firearm-related violence and violence directed at youth and nonwhite individuals. Also, industrial projects that have an environmental impact increase the risk of several types of homicides, but the result is especially consistent for femicides,[13] suggesting that certain development strategies may have unintended harmful social consequences, especially for women, youth, and nonwhite populations.

Second, regarding prioritization of these policies, marginalization is perhaps the first priority, given the consistency of results. However, future research could also clarify the minor reduction in violence according to investment in reducing marginalization, and compare these results with marginal gains from reducing FHHWK, increasing BF coverage, or reducing EI.

Third, regarding policy targeting, the results help distribute resources more efficiently by identifying which policies are more effective depending on type of violence and geographic area. Regarding type of violence, if aggregate homicide rates or the homicide of males only is the primary concern, marginalization and FHHWK are key policy content areas. In contrast, if femicides are the main concern, then policies should focus on marginalization and reducing EI. Alternately, if gun-related, youth, or nonwhite homicides are key concerns, then policies oriented at increasing BF coverage deserve greater attention.

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[13] One illustrative case of the effects of environmental impact is the municipality of Altamira, in the state of Pará. Altamira is the main construction site for the large hydro-electric dam of Belo Monte, on the Xingu River. According to research from the Datafolha Institute, the women in this city are mostly against the construction of the dam, despite the large number of jobs being created, and the main reason given for their opposition is the increase in violence. One of the possible explanations why women are particularly vulnerable to violence is the massive influx to the region of temporary workers, and perhaps also the increase in prostitution that follows large movements of transient workers such as this. See Datafolha Institute; available at: http://datafolha.folha.uol.com.br/opiniaopublica/2013/12/1386247-para-moradores-de-altamira-belo-monte-trouxe-renda-e-problemas.shtml (last accessed Sep. 3, 2014).

In all cases, the results also suggest strategies for geographic targeting, namely, that policies should not be aimed at individual, isolated communities. Rather, violence-prevention and violence-reduction policies—with the content outlined above—should be targeted at groups or sets of relevantly connected communities. In short, violence-reduction policies should have a regional design motivated by the kinds of diagnostics and targeting assessments facilitated by spatial analysis. The LISA values and cluster maps can help guide this geographic targeting, and the results of the spatial regressions—especially the GWR-SL results—fine tune where to target different types of violence for different types of homicides. In this regard, both the cluster maps and the maps of locally varying coefficients identify sets of communities that straddle state boundaries or other relevant administrative or jurisdictional boundaries (e.g., judicial districts, electoral districts). These boundary-crossing phenomena raise a possible barrier of cross-jurisdictional collaboration. Failure to address this kind of collaboration while developing and targeting violence-reduction policies could pose a substantial obstacle for enacting and implementing these policies, especially where key actors on different sides of jurisdictional boundaries (e.g., mayors, governors) are from different political parties.

Lastly, the results also highlight multiple avenues for future research. The uneven patterns of diffusion visualized in Figure 7 (i.e., rho is not always significant, and violence diffuses more intensely in some geographic areas than in others) raise several questions. What are the mechanisms or factors conditioning the intensity of diffusion? What local factors help or hinder diffusion? Also of interest is the evidence that both a spatial error process (common exposure) and a spatial lag process (diffusion) best characterize some types of homicide (men and nonwhite), while only a spatial lag process best characterizes other types of homicide (femicides, gun-related, and youth). The spatial error process may help identify missing or omitted variables and therefore has an important theory-building function. Future research on these issues has much to offer and promises to improve our understanding of the origins of violence, in Brazil and beyond.

REFERENCES

Achen, Christopher H. 2001. "Why Lagged Dependent Variables Can Suppress the Explanatory Power of Other Independent Variables." Paper presented at the annual meeting of Political Methodology. Available at: http://polmeth.wustl.edu/media/Paper/achen00.pdf (last accessed March 25, 2015).

Anselin, Luc. 1988. "Langrange Multiplier Test Diagnostics for Spatial Dependence and Spatial Heterogeneity." *Geographical Analysis* 20 (1): 1–20.

_____. 1995. "Local Indicators of Spatial Association—LISA." *Geographical Analysis* 27 (2): 93–115.

_____. 2005. "Spatial Regression Analysis in R–A Workbook." *Urbana* 51: 61801.

Assunção, Renato M., and Edna A. Reis. 1999. "A New Proposal to Adjust Moran's *I* for Population Density." *Statistics in Medicine* 18 (16): 2147–62.

Ayres, Robert L. 1998. *Crime and Violence as Development Issues in Latin America and the Caribbean*. World Bank Publications.

Bailey, John, and Lucía Dammert. 2006. "Assessing Responses to Public Insecurity in the Americas." In John Bailey and Lucía Dammert, eds., *Public Security and Police Reform in the Americas*. Pittsburgh: University of Pittsburgh Press, 245–61.

Baller, Robert D., Luc Anselin, Steven F. Messner, Glenn Deane, and Darnell F. Hawkins. 2001. "Structural Covariates of US County Homicide Rates: Incorporating Spatial Effects." *Criminology* 39 (3): 561–88.

Barcellos, Christovam, and Alba Zaluar. 2014. "Homicides and Territorial Struggles in Rio de Janeiro Favelas." *Revista de Saúde Pública* 48 (1): 94–102.

Beer, Caroline C. 2003. *Electoral Competition and Institutional Change in Mexico*. Notre Dame: University of Notre Dame Press.

Benítez Manaut, Raúl. 2012. "Encuesta Ciudadanía, Democracia y Narcoviolencia (CIDENA) 2011." Mexico, DF: CEGI, SIMO, and CASEDE.

Brasil, Katia. 2013. "PF Prende 9 Suspeitos de Exploração Sexual de Indígenas No AM." *Folha de São Paulo*, May 23. http://www1.folha.uol.com.br/fsp/cotidiano/110380-pf-prende-9-suspeitos-de-exploracao-sexual-de-indigenas-no-am.shtml.

Brunsdon, Chris, A. Stewart Fotheringham, and Martin E. Charlton. 1996. "Geographically Weighted Regression: A Method for Exploring Spatial Nonstationarity." *Geographical Analysis* 28 (4): 281–98.

Brunsdon, Chris, A. Stewart Fotheringham, and Martin E. Charlton. 1999. "Notes on Parametric Significance Tests for Geographically Weighted Regression." *Journal of Regional Science* 39 (3): 497–524.

Bursik Jr., Robert J., and Harold G. Grasmick. 1999. *Neighborhoods and Crime*. Lanham, MD: Lexington Books.

Buvinic, Mayra, and Andrew Morrison. 1999. *Violence as an Obstacle to Development*. Inter-American Development Bank.

Caldeira, Teresa P. R., and James Holston. 1999. "Democracy and Violence in Brazil." *Comparative Studies in Society and History* 41 (04): 691–729.

Cardia, Nancy, Sérgio Adorno, and Frederico Z. Poleto. 2003. "Homicide Rates and Human Rights Violations in São Paulo, Brazil: 1990 to 2002." *Health and Human Rights* 6 (2): 14–33.

Carvalho, Alexandre, Daniel Ricardo De Castro Cerqueira, and Waldir Lobão. 2005. "Socioeconomic Structure, Self-Fulfillment, Homicides and Spatial Dependence in Brazil." Texto Para Discussão n.1105, no. IPEA.

Ceccato, Vânia. 2005. "Homicide in São Paulo, Brazil: Assessing Spatial-Temporal and Weather Variations." *Journal of Environmental Psychology* 25 (3): 307–21.

Charlton, Martin, Stewart Fotheringham, and Chris Brunsdon. 2009. "Geographically Weighted Regression." White Paper, National Centre for Geocomputation. National University of Ireland, Maynooth.

Cruz, José Miguel. 2008. "The Impact of Violent Crime on the Political Culture of Latin America: The Special Case of Central America." In M. Seligson, ed., *Challenges to*

Democracy in Latin America and the Caribbean: Evidence from the AmericasBarometer 2006–07. Nashville, TN: Vanderbilt University, LAPOP, 219–49.

Deane, Glenn, Steven F. Messner, Thomas D. Stucky, Kelly McGeever, Charis E. Kubrin. 2008. “Not ‘Islands, Entire of Themselves’: Exploring the Spatial Context of City-Level Robbery Rates.” *Journal of Quantitative Criminology* 24 (4): 363–80.

De Souza, Maria de Fátima Marinho, James Macinko, Airlane Pereira Alencar, Deborah Carvalho Malta, and Otaliba Libânio de Morais Neto. 2007. “Reductions in Firearm-Related Mortality and Hospitalizations in Brazil after Gun Control.” *Health Affairs* 26 (2): 575–84.

Dube, Arindraji, Oeindrila Dube, and Omar García-Ponce. 2013. “Cross-Border Spillover: U.S. Gun Laws and Violence in Mexico.” *American Political Science Review* 107: 397–417.

Falleti, Tulia G. 2010. *Decentralization and Subnational Politics in Latin America*. New York: Cambridge University Press.

Farrington, David P., Bernard Gallagher, Lynda Morley, Raymond J. St. Ledger, and Donald J. West. 1986. “Unemployment, School Leaving, and Crime.” *British Journal of Criminology* 26 (4): 335–56.

Fotheringham, A. Stewart, Chris Brunsdon, and Martin Charlton. 2003. *Geographically Weighted Regression: The Analysis of Spatially Varying Relationships*. Hoboken, NJ: John Wiley & Sons.

French, Jan Hoffman. 2013. “Rethinking Police Violence in Brazil: Unmasking the Public Secret of Race.” *Latin American Politics and Society* 55 (4): 161–81.

Gabeira, Fernando. 2011. “O Pulo Do Gato Na Cabeça Do Cachorro.” *Estadao*, December 3. http://www.estadao.com.br/noticias/geral,pulo-do-gato-na-cabeca-do-cachorro,806282.

Gibson, Edward L. 2013. *Boundary Control: Subnational Authoritarianism in Federal Democracies*. Cambridge: Cambridge University Press.

Gonzalez, Samuel. 2013. “Mexican Capo Tried to Escape While Being Captured.” Associated Press, July 17. http://bigstory.ap.org/article/mexican-capo-tried-escape-when-he-was-captured.

Gottfredson, Denise C. 1985. "Youth Employment, Crime, and Schooling: A Longitudinal Study of a National Sample." *Developmental Psychology* 21 (3): 419-432.

Hunter, Wendy, and Natasha Borges Sugiyama. 2014. "Transforming Subjects into Citizens: Insights from Brazil's Bolsa Família." *Perspectives on Politics* 12 (04): 829–45.

Ingram, Matthew C. 2012. "Crafting Courts in New Democracies: Ideology and Judicial Council Reforms in Three Mexican States." *Comparative Politics* 44 (4): 439–58.

_____. 2014. "Community Resilience to Violence: Local Schools, Regional Economies, and Homicide in Mexico's Municipalities." In David A. Shirk, Duncan Wood, and Eric L. Olson, eds. *Building Resilient Communities in Mexico: Civic Responses to Crime and Violence*. Washington, DC: Justice in Mexico Project and Woodrow Wilson Center.

Ingram, Matthew C., and Karise M. Curtis. 2014. "Homicide in El Salvador's Municipalities: Spatial Clusters and the Causal Role of Neighborhood Effects, Population Pressures, Poverty, and Education." Wilson Center, Latin American Program, July. http://www.wilsoncenter.org/sites/default/files/Homicides_El_Salvador.pdf.

Ingram, Matthew C., and Marcelo Marchesini da Costa. 2014. "Targeting Violence Reduction in Brazil: Policy Implications from a Spatial Analysis of Homicide." Policy Brief, Latin America Initiative – Foreign Policy at Brookings, Brookings Institution. http://www.brookings.edu/~/media/research/files/papers/2014/10/02%20violence%20reduction%20brazil%20ingram%20da%20costa/ingram%20policy%20brief.pdf.

Lagos, Marta, and Lucía Dammert. 2012. "La Seguridad Ciudadana. El Problema Principal de América Latina." Santiago, Chile: www.latinobarometro.org.

Lance, Justin Earl. 2014. "Conditional Cash Transfers and the Effect on Recent Murder Rates in Brazil and Mexico." *Latin American Politics and Society* 56 (1): 55–72.

Land, Kenneth C., Patricia L. McCall, and Lawrence E. Cohen. 1990. "Structural Covariates of Homicide Rates: Are There Any Invariances across Time and Social Space?" *American Journal of Sociology* 95 (4): 922–63.

Levitt, Steven D. 2004. "Understanding Why Crime Fell in the 1990s: Four Factors That Explain the Decline and Six That Do Not." *Journal of Economic Perspectives* 18 (1): 163–90.

Lochner, Lance, and Enrico Moretti. 2004. “The Effect of Education on Crime: Evidence from Prison Inmates, Arrests, and Self-Reports.” *American Economic Review* 94 (1): 155–89.

Londoño, Juan Luis, and Rodrigo Guerrero. 1999. “Violencia en América Latina.” Epidemiología y Costos.” BID, Red de Centros de Investigación de La Oficina del Economista Jefe, Documento de Trabajo R-375, Washington DC.

Lu, Binbin, Paul Harris, Martin Charlton, Chris Brunsdon, Tomoki Nakaya, and Isabella Gollini. 2015. “Package ‘GWmodel’.” Available at: http://cran.r-project.org/web/packages/GWmodel/GWmodel.pdf (last accessed March 25, 2015).

Matthews, Stephen A., and Tse-Chuan Yang. 2012. “Mapping the Results of Local Statistics: Using Geographically Weighted Regression.” *Demographic Research* 26: 151.

Mesquita Neto, Paulo. 2005. “Asociaciones Público-Privadas para la Reforma Policial en Brasil: Instituto de São Paulo Contra La Violência.” In Lucía Dammert and John Bailey, eds., *Seguridad y Reforma Policial en Las Américas: Experiencias y Desafíos*. Mexico, D.F.: Siglo XXI, 106–20.

Miller, Ted R., and Mark A. Cohen. 1997. “Costs of Gunshot and Cut/Stab Wounds in the United States, with Some Canadian Comparisons.” *Accident Analysis & Prevention* 29 (3): 329–41.

Naim, Moises. 2012. “La Gente Mas Asesina del Mundo.” *El País Internacional*, 15 December.

Páez, Antonio, Steven Farber, and David Wheeler. 2011. “A Simulation-Based Study of Geographically Weighted Regression as a Method for Investigating Spatially Varying Relationships.” *Environment and Planning-Part A* 43 (12): 2992.

Patrick, Stewart. 2011. *Weak Links: Fragile States, Global Threats, and International Security*. New York: Oxford University Press.

Penglase, R. 2005. “The Shutdown of Rio de Janeiro.” *Anthropology Today* 21 (5): 3–6.

Pridemore, William Alex. 2011. “Poverty Matters: A Reassessment of the Inequality-Homicide Relationship in Cross-National Studies.” *British Journal of Criminology* 51 (5): 739–72.

Putnam, Robert D., Robert Leonardi, and Raffaella Y. Nanetti. 1994. *Making Democracy Work: Civic Traditions in Modern Italy*. Princeton: Princeton University Press.

Raphael, Steven, and Rudolf Winter-Ebmer. 2001. "Identifying the Effect of Unemployment on Crime." *Journal of Law and Economics* 44 (1): 259–83.

Reichenheim, Michael Eduardo, Edinilsa Ramos De Souza, Claudia Leite Moraes, Maria Helena Prado de Mello Jorge, Cosme Marcelo Furtado Passos Da Silva, and Maria Cecília de Souza Minayo. 2011. "Violence and Injuries in Brazil: The Effect, Progress Made, and Challenges Ahead." *The Lancet* 377 (9781): 1962–75.

Rosenfeld, Richard. 2009. "Crime Is the Problem: Homicide, Acquisitive Crime, and Economic Conditions." *Journal of Quantitative Criminology* 25 (3): 287–306.

Ruhm, Christopher J. 2000. "Are Recessions Good for Your Health?" *Quarterly Journal of Economics* 115 (2): 617–50.

Sampson, Robert J. 1986. "Effects of Socioeconomic Context on Official Reaction to Juvenile Delinquency." *American Sociological Review* 51 (6): 876–85.

Sampson, Robert J., and W. Byron Groves. 1989. "Community Structure and Crime: Testing Social-Disorganization Theory." *American Journal of Sociology* 94 (4): 774–802.

Sampson, Robert J., Stephen W. Raudenbush, and Felton Earls. 1997. "Neighborhoods and Violent Crime: A Multilevel Study of Collective Efficacy." *Science* 277 (5328): 918–24.

Santos, Simone M., Christovam Barcellos, and Marilia Sá Carvalho. 2006. "Ecological Analysis of the Distribution and Socio-Spatial Context of Homicides in Porto Alegre, Brazil." *Health & Place* 12 (1): 38–47.

Sarles, Margaret. 2001. "USAID's Support of Justice Reform in Latin America." In Pilar Domingo and Rachel Sieder, eds., *Rule of Law in Latin America: The International Promotion of Judicial Reform*. London: Institute of Latin American Studies, University of London, 47–79.

Schedler, Andreas. 2014. "The Criminal Subversion of Mexican Democracy." *Journal of Democracy* 25 (1): 5–18.

Shaw, Clifford R., and Henry D. McKay. 1969. *Juvenile Delinquency and Urban Areas*. Revised Edition. Chicago: University of Chicago Press.

Shoff, Carla, Vivian Yi-Ju Chen, and Tse-Chuan Yang. 2014. "When Homogeneity Meets Heterogeneity: The Geographically Weighted Regression with Spatial Lag Approach to Prenatal Care Utilization." *Geospatial Health* 8 (2): 557.

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

Thompson, Sara K., and Rosemary Gartner. 2014. "The Spatial Distribution and Social Context of Homicide in Toronto's Neighborhoods." *Journal of Research in Crime and Delinquency* 51 (1): 88–118.

UNODC (United Nations Office on Drugs and Crime). 2013. *Global Study on Homicide 2013*. Available at: http://www.unodc.org/gsh/en/data.html (last accessed February 2, 2015).

Vilalta, Carlos. 2014. "How Did Things Get So Bad So Quickly? An Assessment of the Initial Conditions of the War against Organized Crime in Mexico." *European Journal of Criminal Policy & Research* 20: 137–61.

Wheeler, David, and Michael Tiefelsdorf. 2005. "Multicollinearity and Correlation among Local Regression Coefficients in Geographically Weighted Regression." *Journal of Geographical Systems* 7 (2): 161–87.

WHO. 2002. *World Report on Violence and Health*. World Health Organization.

Willis, Graham Denyer. 2014. "Antagonistic Authorities and the Civil Police in São Paulo, Brazil." *Latin American Research Review* 49 (1): 3–22.

World Bank. 2006. *Crime, Violence and Economic Development in Brazil: Elements for Effective Public Policy*. 36525. Poverty Reduction and Economic Management Sector Unit.

_____. 2014. World Bank Open Data. Available at: http://data.worldbank.org/ (last accessed July 12, 2014).

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.