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A Spatial Analysis of Homicide Across Brazil's Municipalities

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Abstract

Examining homicide across Brazil's 5,562 municipalities, we find that violence nearby has a positive effect on local violence (diffusion effect), violence exerts an unusual negative spatial effect in small clusters of communities in northeastern Brazil, and a prominent poverty-reduction program (Bolsa Família [BF]) has mixed effects. The spatial dimensions of violence complement existing non-spatial research on violence in Brazil, and the results regarding BF offer a spatial complement to research on conditional cash transfer (CCT) programs, clarifying the sources of violence in Latin America's largest country and shedding light on the content and geographic targeting of violence reduction policies.

Keywords

diffusion, GWR, GWR-SL, homicide, mapping, methodology, prevention, public policy, structural causes, spatial, violence

Introduction

Violence in Latin America generates heavy costs for individuals, communities and societies. Building on previous research on the socioeconomic predictors of violence, this study has two aims. First, it examines the spatial diffusion of violence. Second, it examines a major policy intervention aimed at improving socioeconomic conditions and which therefore should have an identifiable effect on reducing violence. Most

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current analyses of violence in Brazil adopt a non-spatial approach, and the few spatial studies of violence focus on one or a limited selection of cities or states. Our spatial analysis of the entire country at the municipal level (covering all 5,562 municipalities) is thus, to our knowledge, the first such analysis. We detect cross-unit patterns of diffusion (where violence in one place spreads or influences violence in nearby places) and causal heterogeneity (where standard predictors and even the diffusion of violence exert an uneven effect across municipalities). While examining this diffusion and heterogeneity, and controlling for standard socioeconomic characteristics of municipalities that are well-documented predictors of violence in non-spatial research designs, we also examine how a prominent conditional cash transfer (CCT) poverty-reduction program (*Bolsa Família* [BF]) affects homicide rates across all Brazilian municipalities.

The article begins with a discussion of case selection and our decision to focus on Brazil. We then outline our theoretical framework, working hypotheses, and the observable, empirical implications that stem from these hypotheses. Next, we discuss our data and methods, including common spatial regressions, geographically weighted regression (GWR), and the less common extension that is GWR with a spatial lag of the outcome of interest (GWR-SL) following Páez, Uchida, and Miyamoto (2002) and Shoff, Chen, and Yang (2014). We then proceed to our analysis. Core results show that homicide in nearby communities increases the homicide rate in one's home, focal community. Furthermore, the effect of homicide in nearby areas—the diffusion effect—also varies across geographic areas. That is, the harmful effect of nearby violence is itself uneven (non-stationary). Also, the proportion of poor, eligible families covered by BF has mixed effects, but these effects are non-significant across most of Brazil, contrasting with existing research.

The discussion and conclusion address policy implications and avenues for future research. On policy implications, the analysis sheds light on interventions aimed at preventing or reducing violence by identifying how such interventions should be tailored by (a) scope (national or local), (b) content (depending on the significance of specific predictors), and (c) geographic location (based on GWR). Regarding opportunities for further research, the findings here could serve as a platform for qualitative, in-depth case studies across Brazil to flesh out more precisely what causal processes are underway on the ground to condition locally varying effects of predictors (e.g., Harbers & Ingram, 2015). In sum, the analysis offers insights for a better understanding of the sources of violence, including structural covariates and institutional policies, and therefore enhances our ability to design and target violence prevention efforts.

Why Study Violence in Brazil?

The intensity of violence in Latin America and the well-known social, political, and economic consequences of violence and insecurity motivate this study. According to some estimates, Latin America holds 8% of the world's population but accounts for 42% of all homicides (Naim, 2012). The United Nations Office on Drugs and Crime (UNODC; 2015) reports homicide rates for the major regions of the world for the 18 years from 1995 to 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 4 to 6 times higher than those in North America. For instance, while the U.S. homicide rate was five per 100,000 in 2010, the rate for Latin America was approaching 30 (UNODC, 2015).

Focusing on Brazil, the country's homicide rate tracks the broader regional rate from 2000 to 2012, making it representative of the region. Brazil had homicide rates similar to the ones from the United States in the beginning of the 1980s, but by the end of that decade had already doubled the American rates (Caldeira & Holston, 1999). For a decade leading up to 2012, the national homicide rate in Brazil stood at more than 20 per 100,000 inhabitants (23.4 in 2011 and 25.2 in 2012), or about 4 times the U.S. rate. This rate is not only higher than most countries in Latin America but also lower than several countries in the region, including several Central American countries, Colombia, Venezuela, and Mexico, so Brazil's violence can be regarded as fairly representative of Latin America as a whole, and findings here can therefore generalize more easily than findings from other countries.

Furthermore, while the worst city in the United States each year has a homicide rate around 50 and only a handful are ever above 40, about 10% of Brazilian cities (541) have homicide rates above 40, and more than 5% of cities (312) have rates above 50. Hundreds of Brazilian cities experience quotidian levels of violence higher than the worst city in the United States. Making matters worse, the real incidence of homicide is overshadowed by the fear of being a homicide victim in Brazil. A 2015 study of more than 80 Brazilian cities showed eight out of 10 people feared being murdered, and a full 20% reported already having received death threats (Vieira, 2015). Aside from the direct harm to health from such persistently elevated violence and insecurity, the real incidence and subjective fear of violence can dampen participation in public life, confidence in democratic institutions, and economic activity (AmericasBarometer, n.d.; Instituto Nacional de Estadistica y Geografia [INEGI], 2015). Furthermore, as Latin America's largest democracy and economy, Brazil's patterns of crime and insecurity are important to understand given its regional and increasingly global prominence.

Beyond the substantive importance of studying homicide in Brazil, the country offers a rich environment in which to examine patterns of fatal violence and proposed policy solutions. First, Brazil is composed of more than 5,000 municipalities, and the availability of comparable demographic and socioeconomic data collected systematically across these municipal units affords a promising setting in which to study the spread of violence across space, as well as the geographically uneven effect of well-known predictors of violence. Second, BF—Brazil's CCT program—is one of the world's first and largest such programs, has been studied for a wide range of reasons, but—with few notable exceptions discussed later—BF has been neglected with regard to its relationship with crime and violence. Thus, conducting this research in Brazil 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—and how a major poverty-reduction program is related with violence reduction within the context of such a spatial approach. 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.

In sum, Latin America has a high homicide rate as a region compared with the rest of the world, and Brazil can be considered typical or representative of this phenomenon in a region marked by such 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 article to the broader literature on the advantages of subnational research (Snyder, 2001). Although diverse, Brazil's municipalities are under a similar institutional framework, and share relatively similar cultural heritages, among other potential confounders. Finally, Brazil is the region's largest country and largest economy in Latin America, and existing research within Brazil notes a marked unevenness in the distribution of homicide (e.g., Cerqueira, 2013, also noting measurement problems; Ingram & Marchesini da Costa, 2014). For all these reasons, Brazil is a promising setting in which to study violence, especially the spatial dimensions of violence.

Theoretical Framework and Working Hypotheses

Building on existing research, we test (1) whether violence diffuses across geographic space, (2) whether a major poverty-reduction program has a helpful effect on violence, and (3) whether there are spatially uneven dimensions in (a) the diffusion of violence and (b) the effects of the poverty-reduction program. Although some existing studies have sought to examine the spatial dimensions of violence in Brazil, these studies tend to focus on a single city or region (e.g., Chioda, de Mello, & Soares, 2015; Simmons, 2004),[1] or are exploratory in nature (e.g., Ingram & Marchesini da Costa). In contrast, we examine all 5,562 municipalities and test for diffusion of violence and whether there is spatial heterogeneity—that is, a geographically uneven effect—in the effect of diffusion and a major poverty-reduction program, as well as other well-known predictors of violence that are controlled for in the analysis.

Spatial Diffusion

A broad range of research areas in the social sciences are increasingly interested in empirical examinations and explanations of the phenomenon of diffusion. Why does an outcome of interest spread from one place to another? For instance, social scientists have long studied the spread of innovations (e.g., Rogers, 2003[1962]) and political scientists have recently studied the spread of various forms of political and economic liberalization (e.g., Simmons, Dobbin, & Garrett, 2008), as well as the spread of ideas (Hilbink, 2012; Ingram, 2016a, 2016c) and criminal justice policies (Ingram, 2016b; Langer, 2007).

The rising theoretical interest in diffusion is especially apparent in the study of crime and violence (Baller, Anselin, Messner, Deane, & Hawkins, 2001; Deane, Messner, Stucky, McGeever, & Kubrin, 2008; Dube, Dube, & Garcia-Ponce, 2013; Tolnay, Deane, & Beck, 1996; Vilalta & Muggah, 2014). That is, we expect an increase in violence in nearby communities to cause an increase in violence in one's home, focal community. Notably, an alternative expectation relates to the rare but intriguing possibility of a negative relationship between nearby violence and local violence. Tolnay et al. (1996) found evidence of this negative spatial effect in their study of political violence in the form of lynchings in the United States, as did Messner et al. (1999) in the identification of U.S. counties that act as "barriers" to violence.

This discussion leads to two contrasting hypotheses and related empirical implications. First, we expect that homicide in nearby locations increases the likelihood of homicide locally. This is the dominant diffusion hypothesis. In the evidence, we should see a positive association between the weighted mean homicide rate among neighboring municipalities and the homicide rate of a focal municipality (this association is captured by the coefficient ρ, or rho, in the methods and analysis discussed later). Alternatively, the second hypothesis is that homicide in nearby locations may decrease the likelihood of homicide locally. This expectation captures the "barrier" phenomenon discussed by Messner et al. or the negative demonstration effect in Tolnay et al. If this expectation is correct, the concrete, observable implication is that we should see a negative association between the neighborhood mean homicide rate and the homicide rate of a focal municipality.

Poverty-Reduction Program (BF)

A major development policy that is geared toward reducing poverty can also be expected to have helpful effects on violence. BF, the largest CCT program in the world as of 2009 and one that covers all 27 Brazilian states (Loureiro, 2013), is widely regarded as a holistic poverty-reduction program in which cash transfers hinge on, among other things, children's participation in school. For these reasons, BF has the potential to prevent, soften, or reverse several predictors of crime and violence (social disorganization, including family disruption), while also improving other preventive factors, including education, employment, and income outcomes.

Indeed, current research indicates participation in CCT programs like BF helps decrease property crime in Colombia (Camacho & Mejia, 2013), and reduce armed conflict in the Philippines (Crost, Felter, & Johnston, 2016). In Brazil, recent evidence from non-spatial research finds that BF increases the sense of belonging and efficacy (Hunter & Sugiyama, 2014), resonating with the sociological literature on the violence reduction effects of collective efficacy, social capital, and community resilience. Other non-spatial research shows BF reduces the incidence of crime in the 27 states (Loureiro) and reduces crime in the city of São Paulo (Chioda et al., 2015). Loureiro's findings are strongest regarding property crime, and he finds no significant findings regarding violent crime, including homicide, and the strength of Chioda et al.'s results is relatively unclear.[2] Closest to the present project is another study, though also non-spatial, showing that participation in BF decreases the incidence of homicide across Brazil's municipalities (Lance, 2014).

Thus, taken together, the current research on CCT programs in general and on BF in particular support the expectation that CCT programs should have a dampening effect on property crime, violent crime, and political violence like armed conflict. Notably, spatial dynamics are absent from these existing studies.

The current study can therefore be seen as offering a spatial extension of current research on the relationship between CCT programs and violence. Although Lance's non-spatial study shows that BF has a uniformly beneficial effect across all Brazilian municipalities when treating these municipalities as independently distributed, the current study treats the municipalities as interdependent and examines whether violence in one place is affected by violence in nearby places and whether predictors of violence, including BF, have a geographically uniform or uneven effect. This potential unevenness is addressed in greater detail below in our expectations regarding spatial heterogeneity.

Spatial Heterogeneity

The literature on subnational politics frequently calls attention to the uneven shape or performance of institutions across a country's territorial units or jurisdictions (e.g., Snyder, 2001). Drawing on this literature—and on the general expectation that the tremendous regional diversity within Brazil likely influences the underlying phenomenon of interest—we anticipate that the diffusion (or barrier) effect hypothesized above (as well as the effect of other predictors of violence present as controls in the analysis) will have an uneven effect across units.

In this regard, we could recast the diffusion effect discussed in the previous paragraph as an expectation about the "spatial homogeneity" of violence, that is, violence in nearby places should lead to similar levels of violence locally, and the hypotheses about uneven or disparate effects discussed here as an expectation about "spatial heterogeneity" (see Shoff et al.). Stated starkly and provocatively, the spatial homogeneity generally associated with spatial autocorrelation approaches to studying diffusion processes may be misguided if diffusion effects may not be uniform across all spatial units. Rather, diffusion may be more pronounced in some places, more or less significant (even non-significant) in some places, and perhaps even reverse direction across space—expressing a positive effect in some places and then a negative, barrier effect in others. Thus, the diffusion effect may be better understood as highly localized homogeneity in a more general pattern of spatial heterogeneity.

In sum, we hypothesize that the diffusion effect that is of core interest in this project may be highly uneven across Brazil's 5562 municipalities. If this hypothesis is correct, the concrete, empirical implication is that we should observe variation in the statistical significance, magnitude, and direction of local estimates of the coefficient capturing the diffusion effect (ρ).[3]

Data and Method

Data

Municipal homicide rates in 2011 constitute the dependent variable, which covers the entire country, specifically, all 5,562 municipalities across 27 states (including the Federal District of Brasilia). Data were obtained from the Brazilian Ministry of Health's System of Mortality Information (*Sistema de Informações sobre Mortalidade*). Although more recent homicide data are available, 2011 was selected as the year in which to measure the outcome of interest because of the proximity of this year to a large number of explanatory variables collected during the preceding 2 years (see below). We used the logged, spatially smoothed version of homicide rates.[4] Given that the smoothed outcome eliminates some of the variation in the dependent variable, it can be harder to find significant results, and is therefore a more conservative approach. Thus, any results that are found should deserve that much more attention.

All the demographic data for explanatory variables 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. Data from the Brazilian Institute of Geography and Statistics (*Instituto Brasileiro de Geografia e Estatística*, IBGE) provide the remaining explanatory variables.[5]

Explanatory variables control for well-established arguments in the literature. Population, population density, percentage of population that is rural, and percentage of population composed of young males capture core population and demographic pressures (e.g., Land, McCall, & Cohen, 1990; Sampson & Groves, 1989).[6] Inequality, marginalization, and employment rates capture socioeconomic conditions and economic activity (e.g., Pridemore, 2011),[7] and measures of family disruption[8] and social capital (density of civil society organizations; civil society participation in government[9]) capture aspects of social organization and collective efficacy (e.g., Sampson & Groves, 1989; Sampson, Raudenbush, & Earls, 1997; Thompson & Gartner, 2014). Although this literature largely comes from the United States, existing studies suggest these factors are relevant globally (Baumer & Wolff, 2014), including Latin America (Londoño & Guerrero, 1999). At a minimum, inclusion of these factors advances comparative scholarship on crime and violence.

Data on BF coverage come from the above-mentioned official profile of municipalities. The variable captures the percentage of families that are eligible for BF who are actual participants in the program ([number of participating families] / [number of eligible families]).

Finally, two controls capture features relevant to Brazil, especially large portions of the country outside the industrialized and more developed southeastern states. First, Environmental impact is a categorical variable capturing the presence of large industrial projects that required clearance through a process of environmental review.[10] These projects can increase the likelihood of disruptive dynamics related to land-based conflicts and violence against indigenous people (Arsenault, 2016; CIMI, 2014). Deforestation associated with large industrial projects like mining, hydroelectric dams, ranching, or large-scale agriculture can also lead to violence (Alston, Libecap, & Mueller, 2000; Sant'Anna & Young, n.d.). Land use variables are increasingly emphasized in crime studies in the United States (e.g., Sparks 2011), and land use has also been included in studies of political violence and violent crime in Brazil (Alston et al., 2000; Simmons, 2004). Second, state capacity[11] captures the strength of local public institutions, and therefore the ability of local institutions to prevent or reduce violence. Existing crime studies in the region include the explanatory role of state capacity (Bergman & Whitehead, 2009).

Method

Spatial analysis lends itself to the study of the diffusion phenomena and uneven causal relationships outlined in the "Theoretical Framework and Working Hypotheses" section. The key analytic benefit of spatial analysis is the explicitly dependent structure of the data, and spatial regressions can 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 for how the magnitude, direction, or significance of predictors and the spatially lagged dependent variable can be uneven across units of analysis.

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

$$y = \rho W y + X\beta + \varepsilon,$$
$$\varepsilon = \lambda W \varepsilon + \mu. \tag{1}$$

In Equation 1, β is a **K** × 1 vector of parameters associated with exogenous variables X, which is an **N** × **K** matrix; ρ is the coefficient for the spatially lagged dependent variable (Wy); λ is the coefficient for the spatially lagged autoregressive structure of the disturbance ε, where μ is normally distributed around zero. W is an **N** × **N** row-standardized spatial weights matrix.

Assuming no spatial autoregressive effects ($\rho = 0$; $\lambda = 0$), Equation 1 reduces to the classic ordinary least-squares (OLS) model. Where there is an autoregressive process in the error term but no autoregressive process in the dependent variable ($\rho = 0$), the model reduces to the spatial error model (SEM). Where there is an autoregressive process in the dependent variable but no autoregressive process in the error term ($\lambda = 0$), the model reduces to the spatial lag model (SLM).

Given that researchers should always test for heterogeneity to strengthen the validity of inferences (Darmofal, 2015) and based on our substantive interest in the uneven effect of both the diffusion effect and other predictors of violence, we test for spatial heterogeneity and, based on affirmative results of that test, build a variant of GWR (Brunsdon, Fotheringham, & Charlton, 1996; Charlton, Fotheringham, & Brunsdon, 2009; Fotheringham, Brunsdon, & Charlton, 2002). Specifically, we follow Páez et al. (2002) and Shoff et al. in specifying a GWR-SL model. In other words, by adding a spatial lag of the outcome of interest—which presumes at least some degree of spatial homogeneity, that is, that the outcome in one place is related to the outcome in nearby places—Páez et al. (2002) and Shoff et al. propose a GWR with a spatial lag of the outcome, calling this GWR-SL, though they take different approaches to estimation (maximum likelihood and two-stage least squares, respectively). Following Shoff et al., we calculate the spatial lag of the outcome (*Wy*) at each location *i* in a first stage, and then estimate a GWR model that includes *Wy* among the predictors in a second stage.[12] Thus, the equation for GWR-SL can be expressed as follows:

$$y_i = \rho_i W_i y + \beta_i X_i + \varepsilon_i, \tag{2}$$

where $W_i y = \alpha_i W_i X_i + u_i$.

In Equation 2, ρ captures spatial homogeneity as the locally varying lag effect of the outcome of interest at each location *i* (where *i* is identified by its geographic coordinates), while β 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. Each location *i* is captured by the latitude and longitude of the centroid of each municipality, and estimating both ρ and β is based on a weights matrix conditioned by other observations in the data set and therefore changes for each location, yielding local coefficients (Brunsdon et al., 1996; Charlton et al., 2009; Fotheringham et al., 2002).

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. Diagnostics did not reveal serious multicollinearity, so this is not a concern here. 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 and Diagnostics

This section develops a spatial analysis in two stages. First, Table 1 reports results from two preliminary analyses: (a) a basic SLM specification (in column A), and (b) simulation-based diagnostic tests that identify which variables have non-stationary effects (column B); these are the tests that motivate the GWR-SL analysis.[13] Second, Figures 1 and 2 visualize the results of the GWR-SL analysis by reporting the locally varying coefficients as maps, maps which show variation in the direction, magnitude, and significance of coefficients. Taken together, the findings from all regressions identify whether homicide diffuses from nearby communities to focal communities, whether BF has a helpful effect on violence, and whether the significance, magnitude, and direction of the diffusion effect also varies across municipalities.

The findings from Table 1[14] should be interpreted by reading columns A and B together. Specifically, if the stationarity test in column B is not significant ($p > .05$), then the relationship is stationary and the coefficient in column A can be read as applying across all of Brazil's municipalities uniformly. That is, the result in column A

Table 1. Spatial Regression and Test for Stationarity.

	Column A	Column B
	SLM	Stationarity test
DV = HR (logged, smoothed, lhreb)		
Variable	Coefficient	*p* value
(Intercept)	−4.776*	.000
Population	−0.032*	.000
Rural pop (%)	−0.043*	.000
Density	0.002	.000
Young males (%)	−0.213*	.000
Inequality	−0.007	.002
Marginalization	0.156*	.000
Female HH with kids	0.003*	.417
Employment rate	0.005*	.008
Civil society	0.013*	.000
Council	0.035	.266
Bolsa Família	−0.001*	.000
Environmental impact	0.070*	.486
State capacity	0.090*	.000
Rho (ρ)	0.492*	.000
N	5,562	Number of simulations: 1,000
AIC	6892.5	
Wald	1168	
LR	−3432.11	
LM	18.14	
Pr(LM)	<.001	

Note. DV = dependent variable; HR = homicide rate; HH = head of household. Standard errors omitted for economy of presentation. SLM = spatial lag model; AIC = Akaike information criterion; LM = Lagrange multiplier.
*$p < .05$.

captures the full nature of the relationship across all of Brazil. In contrast, if column B reports a statistically significant stationarity test ($p < .05$), then the relationship is uneven across Brazil's 5,562 municipalities and the results in column A should be ignored in favor of the GWR-SL results visualized in Figures 1 and 2.

Focusing on our core relationships of interest, column B shows a statistically significant stationarity test for both the diffusion coefficient ρ and for BF, so we hold the discussion of these results until Figure 1. Similarly, several controls also have *p* values below .05 in column B—including all population pressures, inequality, marginalization, employment rate, civil society density, and state capacity—so we wait to discuss these findings until Figure 2.

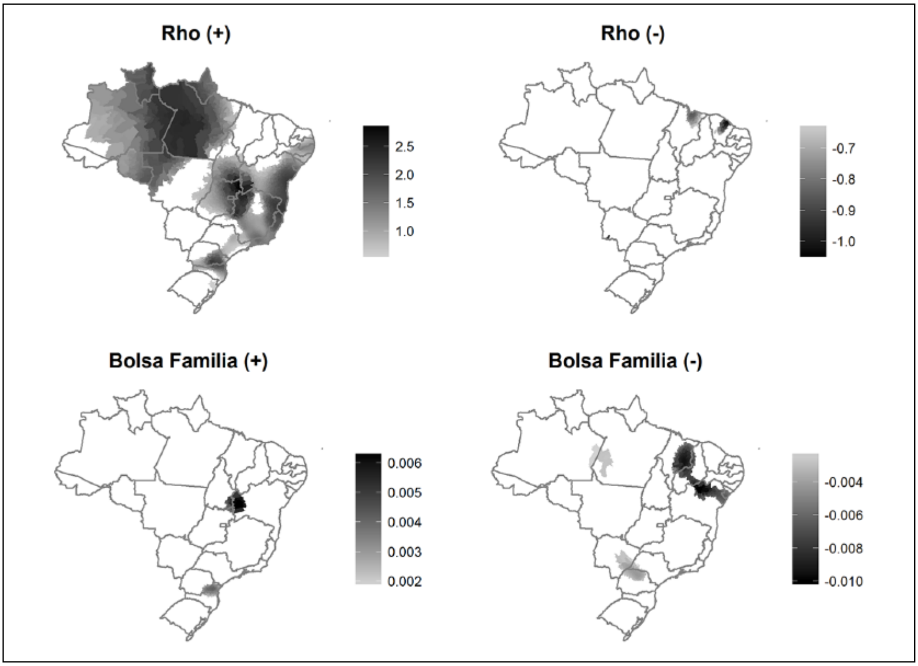

Figure 1. GWR-SL results for lag effect (rho) and BF coverage.
Note. GWR-SL = geographically weighted regression with spatial lag; BF = Bolsa Família.

Both (a) female-headed households and (b) environmental impact have a positive and statistically significant relationship with homicide, and the stationarity tests for these relationships are not significant, so the relationships hold across all of Brazil. Finally, the participation of civil society organizations in municipal government does not have a statistically significant effect, and this relationship is stationary ($p > .05$ in column B), so this non-significance holds across all of Brazil.

Unpacking Key Findings: GWR-SL

Based on the diagnostics in Table 1, column B, we estimated locally varying coefficients for all non-stationary predictors.[15] Maps of the locally varying coefficients help understand the results (Matthews & Yang, 2012). Figures 1 and 2 visualize the uneven effect of non-stationary coefficients, organizing the results by predictor to facilitate interpretation and assessment of expected relationships. We discuss each of the figures below following a similar structure, highlighting the significance, direction, magnitude, and special geographic regions of concern.

Figure 1 reports the GWR-SL results for our two core relationships of interest: rho (spatial lag; first row), and BF coverage (second row). The grayscale maps identify areas where each coefficient exerts a positive effect (left column) and where the

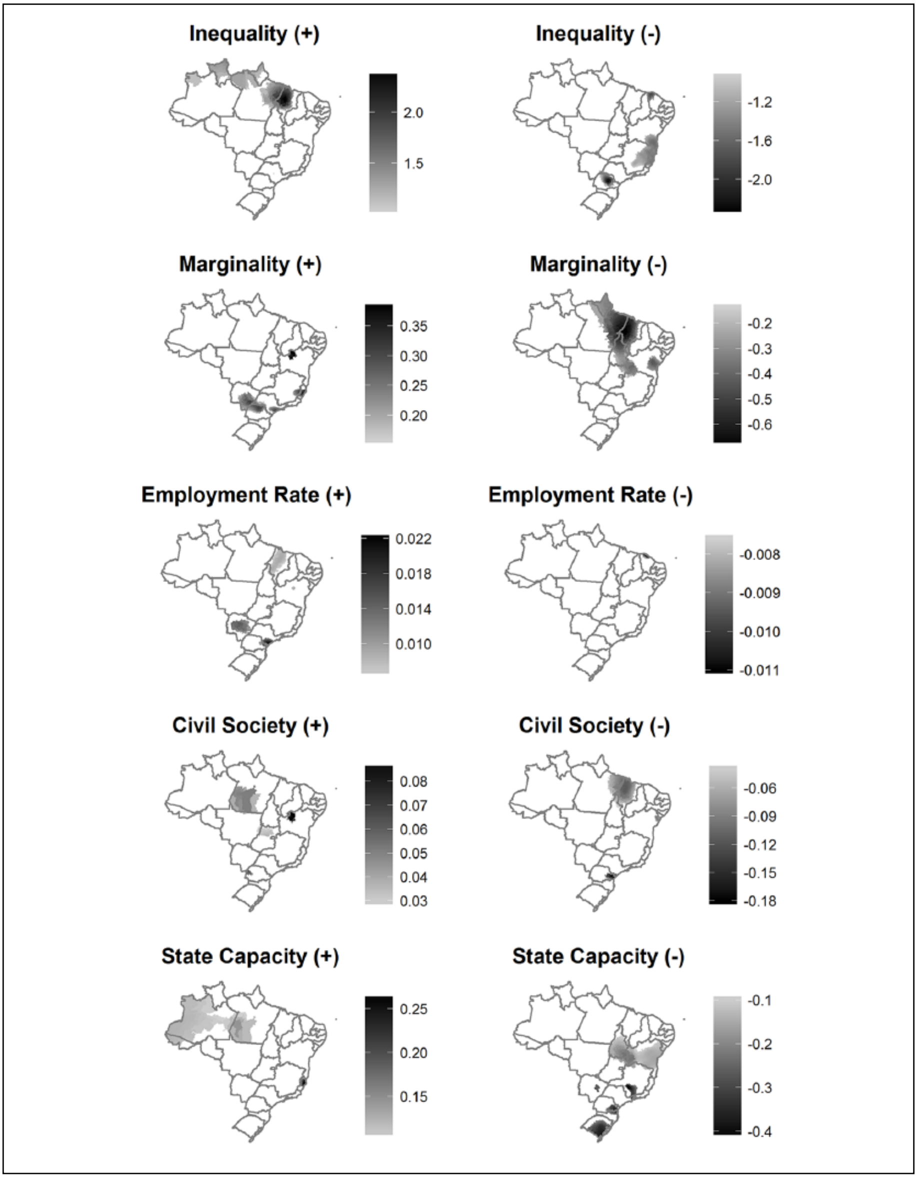

Figure 2. GWR-SL results for non-stationary controls.
Note. GWR-SL = geographically weighted regression with spatial lag.

coefficient is negative (right column). Thus, both columns in each row should be read together to get a full sense of nature of relationship. In all maps, white identifies areas where the relationship is not statistically significant.[16] Taken together, the maps show

how the statistical significance, magnitude, and direction of each effect vary across Brazil's 5,562 municipalities.

The coefficient for the diffusion of violence (rho) is statistically significant throughout nearly the entire country, with the exception of small areas in the south-central and northeastern parts of Brazil where violence in nearby areas does not appear to affect violence in one's home community. The direction of rho is also notable because while it is positive most of the time where it is statistically significant (top left panel in Figure 1), the direction changes to reflect a negative relationship in clusters of municipalities in northeastern Brazil (top right panel). Also, the magnitude of rho's effect varies across space. Regions where rho is most positive include the Amazon, a region north and east of Brasilia; and the central part of the eastern coast, stretching north from Espírito Santo.

Figure 1 also visualizes the local variation in the coefficient for BF coverage (bottom row). This effect is only significant in small areas, and the direction of this effect varies across these areas. BF coverage has the anticipated negative, helpful effect on violence in three clusters: (a) a band of northeastern municipalities stretching across the states of Alagoas, Bahia, Piauí, and Maranhão; (b) a grouping in the Amazon region; and (c) another grouping straddling the borders of the southern states of Paraná, Mato Grosso do Sul, and São Paulo. The magnitude of this negative effect also varies, especially within the northeastern band of communities, exerting the strongest reductive effect on violence in northern Bahia and eastern Maranhão. The direction of this effect reverses and becomes positive in two clusters of states: one straddling the boundaries of the states of Bahia, Tocantins, and Goiás, and the other straddling the boundaries of the southern states of Paraná and Santa Catarina.

Figure 2 reports the GWR-SL results for all non-stationary controls, using a similar scheme. To economize space, we excluded all population variables as policy implications related more directly to other predictors of interest (results regarding population pressures are available from corresponding author). Thus, the five rows in Figure 2 report results for positive effects (left column) and negative effects (right column) for (a) inequality, (b) marginality, (c) employment rate, (d) civil society density, and (e) state capacity. Again, all maps show similar variation in significance, magnitude, and direction.

Discussion

Overall, the results show meaningful variation in the statistical significance, magnitude, and direction of key explanatory variables, and this variation has several implications for policy design and identifies multiple avenues of future research. We also discuss the implications of control variables that exhibit non-stationary effects on homicide.

The diffusion effect captured by rho exhibits a dominant positive direction that supports our core expectation regarding the diffusion of violence. That is, the evidence supports the conclusion that nearby homicide increases homicide locally. Notably, there are large areas of strong diffusion that cross state boundaries, drawing attention to issues of cross-jurisdictional policy coordination if efforts to reduce fatal violence are to be successful. Governors and local authorities of municipalities along state boundaries in these areas of high diffusion need to work together to develop violence reduction policies for the interconnected region, rather than for any one community in isolation.

In contrast, areas where rho is negative indicate resistance to or reversal of diffusion, resembling Messner et al.'s "barrier counties" in the United States or Koesel and Bunce's (2013) "diffusion proofing." These small areas of negative rho challenge our main expectation regarding diffusion and suggest openings for further inquiry. For instance, one could conduct in-depth research across the areas of high diffusion (positive rho), no diffusion (non-significant rho), and blocked or reverse feedback (negative rho) to develop a better understanding of the sources of diffusion (Harbers & Ingram). Research that could identify mechanisms of diffusion would be especially valuable. Alternately, further research in the regions of blocked diffusion could yield valuable insights into the properties of communities that are able to resist the diffusion of homicide, or where the incidence of nearby homicide causes a reduction in local homicide.

Given that these barrier effects suggest there may be a positive, harm-inhibiting factor at work, explanations that might emerge from such research may reveal causes that are undemocratic or otherwise socially or politically regressive. For instance, it may be the case that local elites or regional bosses may inflict a large amount of fatal violence on nearby communities to send a message to their home, local community about the costs of resisting their power. This would be a similar phenomenon to Tolnay et al.'s (1996) demonstration effect of lynchings in the southern United States. As Tolnay et al. argue, the negative spatial effect they find could be explained by two alternatives: (a) Whites inflicting lethal violence perceived Blacks as sufficiently threatened after a lynching nearby, or (b) Blacks reduced any behavior that might trigger additional lethal violence after a nearby lynching. In either case, rather than spreading from place to place, lynching in one place reduced lynching in nearby places. Homicide may be operating in similar ways where we detect a negative rho in Brazil.

Whereas there is strong support for our main expectation regarding diffusion, the evidence regarding BF coverage is more mixed. Yet, the mixed nature of the evidence is itself support for our analytic approach that seeks to identify the locally uneven effect of our core predictors of interest. On one hand, the anticipated negative, helpful effect of BF coverage in three clusters of communities shows that participation in this CCT program decreases fatal violence. In these locations, our findings complement Lance in helping to fill a gap in the literature on the relationship between CCT programs and crime and violence, showing that CCT programs are not only helpful regarding non-violent crime and politicized violence like armed conflict but might also be helpful regarding non-political violence like ordinary homicide. On the other hand, the hypothesized relationship is challenged by the unanticipated results of a positive effect of BF coverage in two clusters of states. One possible explanation arises from routine activities theory (Cohen & Felson, 1979; Sherman, Gartin, & Buerger, 1989). Specifically, a dominant expectation in research on crime used to be that increases in economic activity and affluence should lead to reductions in crime; however, more recent findings have repeatedly found the opposite, suggesting that increasing routine economic activity can generate more targets for criminal activity by increasing the circulation of people, goods, and money, that is, a "target rich" environment, thus leading to the previously counterintuitive rise in crime (e.g., Raphael & Winter-Ebmer, 2001). That is, BF may lead to an increase in the number of suitable targets, and thus to an increase in interpersonal violence. Future research could help understand why BF coverage has this unexpected harmful effect in these two locations. For instance, one promising avenue might be to compare evidence across the two statistically significant clusters in the south. One cluster shows a positive effect while the other shows a negative effect, and yet (a) both clusters are in the same region of the country, and (b) there are portions of each cluster that are in the same state (Paraná), allowing greater control over confounders in a small-*n* comparative research design (Snyder, 2001). Another option would be to disaggregate our outcome of interest here (all homicides) and see whether BF has a differential impact on different types of homicide. For instance, recent findings suggest that BF may have a uniformly negative, helpful effect on gun-related deaths and homicides of youth and non-Whites (Ingram & Marchesini da Costa, 2014). This kind of research can help provide a better understanding of the effect of this prominent CCT program, and how this policy intervention can be better tailored for a full spectrum of criminal and violent behavior, from common theft to political violence. With a finer understanding of the uneven effect of BF coverage, CCT programs might also be recommended as possible policies for combating organized crime.

Several control variables are also of interest and worthy of discussion because they exhibited non-stationary effects. All maps show that each control is statistically significant in less than half of the country's territory, and the direction of the effect of each control varies from positive to negative across space. The positive effect of inequality in various parts of northern Brazil aligns with conventional expectations regarding the harmful effect of income disparity, but the positive relationship between inequality and violence in parts of southern, eastern, and northeastern Brazil challenge expectations. One plausible explanation is that a range of inequality may have the expected positive effect, but severe inequality may have a demobilizing effect, for example, via increased security measures by the wealthy, or by geographic separation between rich and poor, that has the side effect of reducing violence. Routine activities theory—discussed above in regard to counterintuitive results related to BF—supports this. Indeed, results for employment rate in Figure 2 also support this proposition that economic activity has a positive effect on violence. In most cases where the employment rate is statistically significant, it has a positive effect on lethal violence in Brazil, suggesting these are areas where economic activity creates more suitable targets for violent crime. In a similar fashion, moderate inequality might drive crime, but severe inequality might generate barriers to crime or a "target poor" environment.

Marginalization has the expected positive relationship on homicides in several parts of the country—the south, east, and northeast—but marginalization also has an unanticipated negative association with homicides in a large swath of communities extending from the northern states of Amapá, Pará, and Maranhão, through the central states of Tocantins and Goiás, to the eastern state of Bahia. In these locations, marginality has a dampening effect that is equally as puzzling as the dampening effect of inequality discussed earlier. The potential explanation offered for inequality might be plausible here, as well. That is, marginality may be so deep and intense here that it has a demobilizing rather than an activating effect.

Civil society has statistical significance that varies widely, with large sections of the country showing no significant relationship between civil society and homicide. Where significance holds, civil society has the expected negative, helpful effect in Maranhão and the northeastern part of Pará, but has an unexpected positive, harmful effect in several clusters, including southwestern Pará, Bahia, and Goiás. The varying effect of civil society may be due to different types of civil society organizations since some may use more confrontational strategies than others. In the most dramatic cases, conflict between some land rights or indigenous rights organizations and landowners or private enterprise has resulted in violence (e.g., CIMI, 2014). Indeed, since the state of Pará is a key site of these land reform efforts and land-based conflicts (Alston et al., 2000; Simmons, 2004), one promising opportunity for future research that flows from the current study is a comparison across (a) a set of communities in northeastern Pará (where the effect is negative), (b) a set of communities in southwestern Pará (where the effect is positive), and (c) a set of communities in central Pará (where effect is not significant).

Finally, the significance of state capacity varies widely, but the effect is consistently significant across the Amazon and in southern Brazil. Interestingly, the direction of the effect is inverted in these two areas: state capacity has the expected negative, dampening effect on violence in small pockets in the south of the country, but has an unanticipated positive effect on homicide in the Amazon. The most likely explanation for the unexpected positive relationship is the existence endogeneity between state capacity and violence. That is, the positive association is a result of state resources being directed at areas of high violence (i.e., violence leads to more state capacity), rather than state capacity causing an increase in violence (Patrick, 2011). Future research may be able to disentangle this relationship with longitudinal data or with a two-stage approach like the one adopted here to estimate rho. A challenge in a two-stage approach to state capacity is that instruments for state capacity are likely to also be predictors of violence.

Limitations

The added value of GWR is that the technique can help identify the uneven effect of predictors. However, once identified (as done here with the effects of diffusion and BF coverage), this unevenness raises additional questions about the sources of this unevenness, including potential non-linear or interactive relationships. A limitation of this study, therefore, is that these other questions are not examined here. Some readers may fault us for not conducting extensive fieldwork to examine local interactions and conditional relationships that shape the uneven effect of predictors. We see these additional questions as important, but ultimately as beyond the scope of this article. However, we do identify these questions so that opportunities for complementary research are more explicit.

Another limitation is that our GWR approach does not yield precise point estimates. Local estimates of coefficients are based on regional regressions of observations within a moving window of communities, weighting closer communities more than distant ones (see discussion of methods). Thus, the estimates are not precise for each individual municipality and should not necessarily be used to single out individual cities. However, the findings and discussion highlight regional variation, and these regional results can be used to identify regional areas of emphasis for different policy interventions or future research.

Regarding data and measurement, a limitation of the current study is that the outcome of interest is the aggregate combination of all homicides. A strength of this approach is that it offers a first, overall view of the sources of homicide. However, a weakness of this approach is that different explanatory factors may have greater or lesser traction for different types of homicide. Future research that disaggregates the outcome of interest into discrete subcategories of homicide would help elucidate how well explanations travel across different types of homicide.

Finally, our data cover only a single year. Longitudinal data could help examine changes over time and other temporal dynamics. However, a challenge that is likely to persist for any longitudinal study of violence is that predictors are available primarily from census data collected around decennial years. Studies that leverage evidence other than administrative data, for example, remote sensing to capture state capacity or land use, may be able to advance longitudinal studies of violence.

Conclusions and Implications

As noted at the outset, violence generates heavy costs for individuals, communities, and societies in Latin America. Seeking a better understanding of the sources of violence to help combat violence, this study presents a spatial analysis of homicide rates across Brazil's 5,562 municipalities with three core results. First, violence in nearby states is associated with violence locally across most of Brazil. Second, this association between nearby and local violence is highly uneven across Brazil; it is positive in most of Brazil (diffusion effect), but is negative in two small clusters in northern Brazil, and is not significant in several regions. The non-significant locations suggest a local blocking mechanism that prevents violence from spreading from one place to another, while the negative relationship suggests a reverse feedback mechanisms that not only prevents violence from spreading but also causes violence to drop locally following the incidence of nearby violence. Each of these phenomena—diffusion, blocking, and reversal—deserves further attention, and future research that can identify causal mechanisms or pathways underlying each phenomenon promises valuable contributions.

Third, a prominent CCT program (BF) has a non-significant relationship with violence across most of Brazil, contrasting with recent non-spatial research (Loureiro;

Lance; Chioda et al., 2015). Furthermore, where significance holds, BF has mixed effects, exerting the anticipated negative, helpful effect in a sizable region of communities, but exerting an unexpected positive, harmful effect in several clusters of communities. Further research is required to clarify the nature of the relationship between CCT programs and violence, but the findings here suggest that research geared toward understanding conditioning factors that shape the uneven effect of BF is a promising avenue for future study.

Several of our control variables also exhibited uneven effects across Brazil's municipalities, including inequality. Although a control, we highlight inequality here because some of the results cut against dominant expectations. Inequality has the expected positive, harmful effect on violence in much of northern Brazil. However, inequality has a surprising negative, dampening effect in several clusters of communities. This latter result is puzzling, given the dominant literature on the harmful effects of inequality. Future research that clarifies this localized phenomenon would be valuable.

Notably, not all of our controls exhibit uneven effects. Predictors that have a significant and uniform, stationary effect on violence include family disruption and environmental impact. Notably, both family disruption and environmental impact have positive, harmful effects. The effects of family disruption and environmental impact were expected. The finding regarding environmental impact is especially provocative given concerns about how to balance economic development with sustainability and citizen security. Our findings suggest that industrial promotion with environmental impact generates insecurity, and this relationship holds across all of Brazil.

We also identify promising opportunities for future research that flow from our findings, and identify limitations to help guide researchers on how to improve on our research design. Overall, our findings help identify the content of policies aimed at reducing or preventing violence, and also help identify strategies for targeting these policies. For instance, the diffusion effect calls for analysts and policy makers to aim violence-related policies at groups or regions of communities rather than at any one community in isolation. This region-based approach could complement the place-based approach to crime reduction well-established in existing scholarship (e.g., Sherman et al., 1989) and that in 2015 to 2016 was heavily emphasized at top policy levels regarding U.S. assistance in Latin America (Brownfield, 2015). Furthermore, the results help distribute resources more efficiently by identifying which specific causal factors to target in different geographic areas. These insights can help address problems of violence and insecurity that plague Latin America and the Caribbean more than any other region in the world.

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Notes

1. Chioda, de Mello, and Soares (2015) use geo-referenced crime data but their empirical strategy does not use spatial econometrics.
2. Specifically, in what Chioda et al. themselves identify as the best-specified models, the results regarding property and violent crimes are significant only at .10 level (Chioda et al., Table 4), and the authors "do not attach too much weight" to the most significant results regarding drug-related crimes because of the small number of non-zero observations for drug-related offenses (Chioda et al., Note 10).
3. Similarly, we should also observe this heterogeneity in the coefficients capturing significance, magnitude, and direction of the effect of other predictors of violence present as other explanatory variables in the analysis.
4. Our spatially smoothed variable is the Empirical-Bayes standardized homicide rate following Assunção and Reis (1999). The standardized or "smoothed" rate takes into account the non-constant population at risk in each unit, adjusting for the fact that units with very small populations and a small number of homicides may generate a high raw rate while units with very large populations and a large number of homicides may generate a small raw rate.
5. United Nations Development Program's (UNDP) Atlas is available at http://atlasbrasil.org.br/2013/pt/download; Brazilian Institute of Geography and Statistics (*Instituto Brasileiro de Geografia e Estatística*, IBGE) data on non-profits 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.
6. Population and the percentage of the local population living in rural settings are variables taken directly from official data. Dividing population by the territorial area of a municipality generates population density, and the proportion of the population that is young and male captures all males aged 18 to 29 years as a percentage of municipal population. All population figures were logged.
7. The official gini index is our measure of inequality; marginalization consists of the principal component of poverty, literacy, and eligibility for Bolsa Família (BF); and the employment rate is for all adult males aged 18 or more.

8. Our measure of family disruption is a categorical variable that captures female-headed households with women who have no education, work, and have children aged below 15 years at home.
9. The number of civil society organizations divided by the population captures the density of these organizations (this measure is logged), and we use the presence of one or more of these organizations on local development councils (Councils) as our measure of civil society participation in local government.
10. This variable captures the presence of projects with legally required environmental impact assessment and licensing through Brazil's national environmental protection agency—the Brazilian Institute of the Environment and Renewable Natural Resources (Instituto Brasileiro do Meio Ambiente e dos Recursos Naturais Renováveis [IBAMA], 2016).
11. State capacity is a principal component of public service provision, including the provision of electricity and water, sewerage, and garbage collection.
12. Using lagged values of predictors is a standard approach in analysis of dependence (Anselin & Rey, 2014; Dow, 2007; Kelejian & Robinson, 1993). 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 of other predictors (Achen, 2000). Another challenge is that Wy and ε are endogenous. Solutions to this challenge include maximum likelihood estimation (MLE; Páez, Uchida, & Miyamoto, 2002), two-stage least squares estimation (2SLS; Shoff et al., 2014), and generalized method of moments estimation (GMM; Anselin & Rey, 2014). Here, we initially estimated the model with a simple spatial lag of y, that is, ignoring the endogeneity based on the fairly large number of cases, and then we also estimated the 2SLS model as a robustness check using lagged versions of the explanatory variables as instruments (Anselin & Rey, 2014). Core results regarding spatial diffusion and the unevenness of this diffusion do not change across specifications and are highly correlated (r = .67), but we present only the 2SLS estimates because this approach is technically more correct, this strategy matches that of a previous study using a GWR-SL (geographically weighted regression with spatial lag) model (e.g., Shoff, Chen, & Yang, 2014), and for economy of presentation. For comparison of estimates with simple lagged y and 2SLS estimates, see website of corresponding author (http://mattingram.net/).
13. All tests executed in R using package "GWmodel," Version 1.2-3 (Gollini, Lu, Charlton, Brunsdon, & Harris, 2015).
14. Only the spatial lag model (SLM) model is reported as Lagrange multiplier (LM) tests indicated a stronger presence of a spatial lag process than a spatial error process (Robust LM lag test = 141; Robust LM error test = 12), and the SLM generated the lowest Akaike Information Criterion (AIC) value (6892.5), indicating it was the model among OLS (AIC = 7843.1), spatial error model (SEM; AIC = 6926.8), and SLM options that best fit the data. The SLM model is also the basis for later GWR-SL models.
15. Bandwidth was 676; AICc (small sample bias corrected AIC) of GWR-SL model (6375.07) is substantially lower than AIC of global OLS regression (7843.1), SLM (6892.5), or SEM (6926.8), supporting choice of GWR-SL model (see Note 14). ANOVA comparison of OLS and GWR (Brunsdon, Fotheringham, & Charlton, 1999) shows GWR is preferable to OLS ($p < .01$).
16. Alternative visualizations of results, including color images and three-dimensional (3D) visualizations (and accompanying R code), are available on personal website of corresponding author (http://mattingram.net/).

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