Social disorganization and homicide mortality rate trajectories in Brazil between 1991 and 2010

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ABSTRACT

Since the 1990s, researchers have noted declining trends in crime and violence, particularly homicide, in Western countries. Studies have explored national and sub-national trends using latent trajectory analysis techniques and identified several factors associated with declining and/or increasing trajectories. Social disorganization (SD) has been consistently linked to increases in homicide rates over time, explaining at least some of the spatial and temporal heterogeneity of homicide. Similar studies have not yet been carried out in Latin America's cities. In this paper we use Group Based Trajectory models to study homicide mortality rate [HMR] trajectories in Brazilian municipalities between 1991 and 2010. Then, through binary and multinomial logistic regression we investigated the association between SD in 1991, and the likelihood of an increasing HMR trajectory. We carried out an ecological time series study using all Brazilian municipalities in the period between 1991 and 2010 (n = 4491). Data on homicide deaths were collected from the Mortality Information System of the Ministry of Health and standardized by age to calculate HMR per 100,000 population. Socioeconomic and demographic data for 1991 were used to compose the composite measure of SD. Our results highlight the spatial and temporal heterogeneity of homicide mortality in Brazilian municipalities. While national trends are steadily increasing, disaggregating municipal trajectories shows that this is driven by a small proportion of municipalities in the country. We found that SD is associated with an ascending homicide trajectory. This result generally supports the notion that poor social structural conditions can create 'space' for criminal behavior and groups and, consequently, violent death.

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1. Introduction

The 1990s represented a major shift in crime and homicide trends in western countries (Tseloni et al., 2010; Weiss et al., 2016). In the US, many cities showed significant reductions in the levels of violence and homicide, with the most famous being New York City's dramatic 73% decline in homicide between 1990 and 2000 (Messner et al., 2005; Baumer and Wolf, 2014). It seems, however, that this movement is not homogeneous, as researchers have found differential patterns between cities and population groups. The examination of shared trajectories of interpersonal violence and homicide reduction is now a topic of special attention. The task is

no longer to understand and explain why homicide rates vary between different areas or clusters in space but also to recognize the existence of heterogeneity between and within the same areas over time, and to understand the factors associated with differential trends (McCall et al., 2011; Cerda and Concha-Eastman, 2011; Griffiths and Chavez, 2004; Kubrin and Herting, 2003; McDowall and Loftin, 2009; Stults, 2010; Parker et al., 2016).

Researchers have modelled homicide trajectories within and between communities using analytical techniques and criminological theories derived from developmental psychology. The idea is that communities as well as individuals go through different developmental stages and can adopt distinct 'careers' in crime and violence (Bursik and Grasmick, 1992; Fagan and Davies, 2004; Schuerman and Kobrin, 1986). Studies using latent trajectory techniques have made it possible to identify the existence of heterogeneity in the evolution of homicide rates in intra-urban space (Griffiths and Chavez, 2004; Stults, 2010). Stults (2010) found significant variation in homicide trajectories across Chicago

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neighborhoods, and investigated the extent to which the differences can be explained by initial socioeconomic conditions. He concluded that social disadvantage is associated with a greater chance of an upward or persistently high homicide rate trajectory.

Very few studies, however, studied homicide trajectories on the city level (McDowall and Loftin, 2009; McCall et al., 2011; Parker et al., 2016). McCall et al. (2011) identified four distinct trajectory groups among 157 large US cities and found that social disadvantage and social disorganization are associated with a higher homicide trajectory group. Heterogeneous homicide trajectories were also found among blacks and whites in US cities (Parker et al., 2016). These studies highlight the importance of local level analysis (Parker et al., 2016). As far as we know, however, no study has been conducted in cities outside the US using this methodology.

Latin America, and Brazil specifically, does not seem to share in the declining trajectories described in the US and other western countries. Since the 1990's Brazil has been recognized as one of the most violent countries in the world, with the total number of homicide death exceeding 50,000 each year since 2008. According to the World Health Organization (Krug et al., 2002), by the end of the 1990s, Brazil had the third highest Homicide Mortality rates (HMR) in the Americas (23 per 100,000 inhabitants). More recent descriptive studies of homicides in Brazil have highlighted changes in trends between regions, states, and capitals (Waiselfisz, 2008; Andrade and Diniz, 2013). Even so, studies that analyze homicide trends in Brazilian municipalities are rare. Furthermore, there is no research that explores and explains different trajectories of homicide in Brazilian municipalities from a social ecological perspective.

Social disorganization (SD) theory is a dominant theoretical perspective that aims to explain the spatial concentration of crime and violence within cities (Bursik, 1988; Kubrin and Weitzer, 2003) focusing on the role that ecological conditions play in hindering or weakening the capacity of a community to attain common goals and engage in effective social control (Bruinsma et al., 2013; Kubrin and Weitzer, 2003; Sampson and Groves, 1989). Social networks, ties, and capital are key features necessary for communities to supervise peer groups, facilitate cooperation, foster mutual trust, and ultimately control crime (Kawachi et al., 1999). Specifically, the theory proposes that social structural conditions such as poverty, ethnic heterogeneity, and family disruption, weaken the ability of communities to build and maintain social ties and collectively supervise and regulate social norms, consequently increasing community vulnerability to crime and victimization (Sampson et al., 1997; Kawachi et al., 1999).

In many Latin American cities including in Brazil, high levels of violence are strongly linked to organized crime and gang activity (Ceccato et al., 2007; UNODC, 2014; Zaluar, 2010; Peres et al., 2016). SD creates favorable conditions for the emergence and consolidation of organized crime groups and gangs (Oliveira et al., 2015) once residents in disorganized areas lack the collective capacity to confront criminal groups (Rengert et al., 2005). In addition, socially disorganized communities in Brazil are often ignored by state institutions and subject to arbitrary or repressive security policies and policing tactics (Cardia et al., 2003). Police violence, in turn, can undermine the legitimacy of state actions among the population (Kane, 2005; Nivette, 2016). When these mechanisms of social control are weakened, residents in disadvantaged neighborhoods must rely on illegal and violent forms of conflict resolution, which would explain to some extent the unequal growth of crime and violence (Kubrin and Weitzer, 2003; Messner et al., 2004; Nivette, 2014).

In summary, two theoretical pathways may link SD and high HMR. The first suggests that structural characteristics of disorganization can compromise community social controls and increase vulnerability to crime and violence. The second is based on the finding that poor access to state security services and exposure to police misconduct are often disproportionately concentrated in poor, socially disorganized communities. The resulting security gaps can motivate individuals and groups to seek justice and solve problems using extralegal, sometimes violent methods. In both cases, i.e. weakened social capacity and the absence of legitimate state security, SD can create 'space' for organized criminal groups, and their associated lethal violence, to emerge and flourish, increasing crime, violence and homicide rates.

According to Kawachi et al. (1999), the level of crime can be considered an indicator of the health of societies. The same can be said about violence and, ultimately, about homicide. Scholars argue that violent crime could be an important concept to understand health inequalities. The idea is that the level of violent crime is an indicator of collective wellbeing, as it is associated with high social disorganization, low social capital, and high relative deprivation. Tagaki et al. (2012) state that crime victimization is, by itself, an important public health issue, given that contextual determinants of crime and violence and health overlap. As such, the study of contextual factors associated with crime and violence can contribute greatly to our understanding of health disparities (Tagaki et al., 2012).

This paper makes two contributions to the understanding of HMR in developing countries. First, we explore municipal criminal 'careers' by investigating the heterogeneity of HMR trajectories in Brazilian municipalities over a 20-year period. In doing so, we use group based trajectory modeling techniques to identify groups reflecting distinct temporal patterns of urban lethal violence between 1991 and 2010. Second, we use the resulting groups to investigate the association between SD and increasing HMR trajectories. We expect that SD increases vulnerability to criminal and violent activity, therefore increasing the likelihood of escalating homicide mortality rate trajectories.

2. Materials and methods

2.1. Data

The dependent variable is the age-standardized HMR per 100,000 population for all municipalities in Brazil between the years 1991 and 2010 (n = 4491). Brazil is legally divided in Regions, States and Municipalities. A Municipality can comprise urban areas (cities), rural areas and, in some cases, different smaller cities. Official data are available for Municipalities, the smaller political and administrative area in Brazil. The municipalities created after year 1991 were excluded (n = 1074) to avoid issues related to missing data and an interrupted time-series. Data on deaths due to homicide and external causes (EC) with undetermined intent (UI) were obtained from the Brazilian Mortality Information System of the Ministry of Health (SIM-MS) for each city and year, resulting in a total of 89,820 data points. In Brazil, it is mandatory that all deaths due to EC be subjected to a necroscopic examination by a coroner in order to define the cause of death (i.e. accident, suicide, or homicide/aggression) according to the 10th Revision of the International Classification of Diseases (ICD-10).

Issues on the quality of homicide mortality data have been recognized in Brazil since the early 1990's, particularly in relation to the failure to establish the intentionality of the violent act that resulted in the death. In such cases death is classified as UI and is coded under the ICD-10 code Y10-Y34. As a result, the numbers of homicide are underestimated due to misclassification, which can bias time series analysis, as it has a direct effect on homicide trends (Cerqueira, 2012). In order to account for this potential bias, all cases coded following the ICD-10 classification as X85-Y09 (Aggression) or Y10-Y34 (UI) were included in our study. Data were collected by age groups (0—4; 5—9; 10—14; 15—19; 20—29; 30—39;

40–49; 50–59; 60 plus).

Soares-Filho et al. (2016) compared different methods to correct EC death and EC mortality estimates in Brazil, such as the collection of additional information in the field, reclassification based on the proportion of EC due to UI, and statistical modeling. The authors conclude that no single technique is clearly superior to the other. Since our main interest is the study of homicide trajectories, which are highly influenced by changes in the quality of death classification over time, we chose to adjust for this issue by reclassification based on the best quality information on external deaths due to UI.

We first calculated the proportion of deaths due to UI by age group in each city from 1980 to 2010. The year 2010 was used as a reference because it is assumed to have the best quality of information. Then for each year and age, in the municipalities with a *higher* proportion of deaths due to UI compared to 2010, deaths were reclassified so that the proportion of homicides were the same as in 2010. For example: in the city X, for 15-29 year-olds, 10% of the deaths due to external cause were classified as UI in 2010. In 1980, the proportion of UI in the same city and age-group was 25%. We reclassified the excessive number of UI deaths as homicide, thus reducing the proportion of UI deaths in 1980 to match 2010 (10%) and increasing the number of homicide deaths. In this way we were able to minimize bias in the time-series resulting from the under-estimation in the number of homicides due to incorrect classification.

Age-standardized HMR residents were calculated for each municipality and year. We used the year 2000 World Health Organization's standard population for the direct standardization rates. Data on population size were drawn from the Census for the years 1991, 2000, and 2010 and projections were obtained from the SIM-MS.[1]

The explanatory variables were selected to reflect key dimensions of SD, including social, structural, and economic disadvantage. Sampson and Groves (1989) identify several exogenous sources of SD that affect the structure and strength of social ties as well as the ability to control crime: socioeconomic status [SES], residential mobility, ethnic heterogeneity, family disruption, and urbanization. We include nine indicators of SES that reflect dimensions of economic disadvantage and deprivation (per capita income, absolute poverty, and infant mortality rate), education (young children out of school, adolescents and youth who completed schooling, and illiteracy), and poor living conditions (water supply, electricity). Educational attainment is considered a traditional component of SES and social stratification (Adler and Ostrove, 1999), and has been associated with significantly lower levels of social trust and civic engagement (Kawachi et al., 1999). Poor living conditions, including lack of access to water and electricity, are often considered social structural characteristics of slums or *favelas* (Unger and Riley, 2007), the residents of which face significant barriers to social mobility, status, and developing social capital (Perlman, 2006). Family disruption is measured using an indicator capturing the structure of households (houses headed by lower educated women).

Household structure impacts the collective capability of parents to supervise their own children and other problematic groups in the community (Sampson and Groves, 1989). Ethnic heterogeneity is measured using the percentage of population that is black. Finally, a measure of urban population is used to reflect the impact of urbanization on the disruption of social ties and capital. In addition to the dimensions of social disorganization outlined above, we include two factors that have been shown to diminish social cohesion and disrupt community social processes: unemployment and inequality (Kawachi et al., 1999; Kubrin and Weitzer, 2003).

Finally, we include the percent youth and percent elderly, which

previous research in Brazil has found to significantly correlate with homicide rates (Cardia et al., 2003). Socioeconomic and demographic indicators for the year 1991 were collected from the SIM-MS and the United Nations Development Programme's Atlas of Human Development in Brazil (Table 1).[2]

In order to avoid multicollinearity among the independent variables, we conducted an exploratory factor analysis to reduce the dimensions into one aggregate indicator (McCall et al., 2010) comprising the structural, social, and demographic characteristics of SD. Furthermore, by combining these dimensions of SD, we are able to capture the theoretically relevant *combined* effect of social-structural disadvantages on community social capital (Kubrin and Weitzer, 2003).

Principle-component factor analyses revealed a multi-factor solution. The first factor included dimensions of socioeconomic status (education, poverty, living conditions) as well as houses headed by low schooling women and percentage of population identified as black (alpha = 0.95). Unemployment, percent elderly, percent youth, and Gini did not load onto the first factor and so were excluded from the composite SD score. The SD score was then transformed into an ordinal variable at the 33rd percentile, creating 'low', 'medium', and 'high' categories of disorganization.

In order to ensure that the results are not affected by omitted variable bias, we re-estimated each model using a global *cumulative disadvantage* score, which incorporated unemployment, Gini, percent youth and percent elderly into the SD score. The results are substantively similar (results available from the authors upon request).

2.2. Data analysis

Descriptive analyses were conducted to evaluate the dispersion of variables among selected municipalities and to investigate the extent to which selected and excluded municipalities differ systematically. P-values for the differences were calculated using the Wilcoxon non-parametric test.

To investigate the heterogeneity among trajectories we used *Group Based Trajectory Modeling (GBTM)*, a semi-parametric approach that identifies *clusters* of trajectories (Nagin, 1999). Initially developed for the study of individual-level behavioral patterns, GBTM is increasingly used in ecological studies to analyze crime and homicide trajectories (Stults, 2010; Cerda and Concha-Eastman, 2011; Griffiths and Chavez, 2004; McCall et al., 2011; Parker et al., 2016). GBTM identifies clusters of trajectories and estimates the probability that each municipality is likely to be part of each discrete trajectory cluster identified.

In order to smooth the time series, we calculated the moving average of the age-standardized HMR for every 3 years. The dependent variable was the moving average of the HMR with a normal censured distribution to allow for a cubic curve function. The independent variable was the corresponding year.

To investigate the association between the trajectories and SD measured in 1991, we compared groups with similar starting values for HMR but with diverging trajectories. In models where initial homicide levels were not similar we controlled for HMR at 1991. We used binary and multinomial logistic regressions to estimate the effect of SD on the likelihood of a municipality experiencing a stable or increasing trajectory. In all models we control independently for the population size. Four models were built: Models 1 and 2 are estimated using logistic regression (LR) techniques. They include SD and population size as independent variables. Models 3 and 4

Table 1
Social, structural, and demographic indicators used in the analysis.

Social disorganization characteristics	Sub-dimension	Indicator
Socioeconomic status	Poverty	Per capita income*
		Absolute poverty: proportion of people with income less than R$ 140,00/month (based on values from august 2010)*
		Infant (0—1 years) Mortality rate: deaths per 1000 live births*
	Living conditions	Water supply: people living in house with water supply (%)*
		Electricity: people living in house with electricity (%)*
	Education	Children 6-14 years-old out of school (%)*
		Adolescents between 15 and 17 years old who completed fundamental schooling (%)*
		Youth between 18 and 24 years old who completed fundamental schooling (%)*
		Illiteracy among those 15 years old or more (%)*
Family disruption	Supervision	Houses headed by lower educated women with at least one child less than 15 years-old (%)*
Ethnic heterogeneity		Black population (%)**
Urbanization		Urban population*
Employment		People older than 16 years-old who are unemployed (%)**
Relative deprivation	Inequality	Gini Index*
Other variables		
		Elder population (>65 years-old) (%)**
Demographic controls		Youth population (15-24 years-old) (%)**
		Resident population**

Source: * United Nations Development Programme's Atlas of Human Development in Brazil. ** Ministry of Health Information System

are estimated using multinomial logistic regression (MLR) techniques and they include SD, population size and homicide rate in 1991 as independent variables.

In addition, we estimated the predicted probability that a municipality with low, medium, or high SD would experience a stable or increasing homicide trajectory, holding all other variables at their means for all models and key independent variables.

Ethics: All the information used in this paper was collected from public secondary on-line official data sources. No individual information was available that could make it possible to identify research subjects. Our analysis was exclusively based on aggregate data.

3. Results

After exclusion of the 1074 newly created municipalities, the estimated number of homicides fell from 913,443 to 882,005. Every excluded municipalities had at least one homicide in the period. Among the included municipalities, only 1.3% (n = 59) did not have any homicides. The differences between included and excluded municipalities were higher at the end of the time-series. (Table 2).

Excluded municipalities have lower HMR, lower population, less urbanization, lower unemployment, lower access to water and electricity supply, and score higher on indicators of SD (Appendix Table 1). Thus the results are likely to be biased towards larger, more socioeconomically developed urban municipalities.

3.1. Heterogeneity in homicide trajectories among Brazilian municipalities

The minimal number of trajectories that best fit our data was estimated using the Bayesian Information Criterion (BIC), beginning by increasing the number of optimal groups from 1 (BIC for 1 group = −327332.83). Following Nagin's (1999) recommendation, we selected the final model with 9 unique trajectories based on the lowest BIC value (BIC = −289349.51). The BIC value was smaller for models with 10 and 11 groups, however the reduction was minimal. In addition, there were no substantive differences between models with 9, 10, and 11 groups. The nine groups reflected distinct levels and trajectories of HMR (Fig. 1). The posterior probability of group membership varied from 90.3% in Group 4, to 97.2% in Group 9.

Groups 1 and 2 comprise 9.44% and 9.86% of included

Table 2
Homicide count and rate for total (n = 5565) and included (n = 4490) Brazilian municipalities.

All municipalities (n = 5565)	1991	2000	2010
Homicide count	33721	47876	53214
Homicide mortality rate (mean)	12.32	12.89	17.26
Std	17.39	18.57	19.99
Min	0	0	0
Max	168.07	201.46	216.03
25th percentile	0	0	0
50th percentile (median)	5.76	5.67	12.3
75th percentile	19.11	19.59	26.27
Included municipalities (n = 4490)			
Homicide count	33715	46205	50632
Homicide mortality rate (mean)	12.32	13.11	17.68
Std	17.39	17.44	19.45
Min	0	0	0
Max	168.08	157.84	216.03
25th percentile	0	0	0
50th percentile (median)	5.76	7.4	13.05
75th percentile	19.11	19.96	26.22

Note. Std = Standard deviation.

municipalities (Table 3). In 1991, both groups start at very low levels of HMR on average (1.24; 0 per 100,000). However, in the mid-1990s, homicide trajectories diverge, wherein municipalities in Group 2 experience an increase in HMR to an average of 12.42 in 2010. By contrast, municipalities in Group 1 maintain a relatively stable, low HMR, increasing only slightly to an average of 2.89 in 2010. Municipalities in Groups 1 and 2 differ on SD and demographic characteristics. Group 1 municipalities have on average smaller populations and lower SD scores.

Groups 3, 4, and 6 collectively comprise over half of the included municipalities (62.32%). All three groups have on average medium levels of HMR in 1991 (10.88; 8.40; 13.84). Groups 4 and 3 maintain relatively stable or marginally increasing trajectories throughout the 1990s and 2000s. Municipalities in Group 3 had on average an HMR of 16.61 in 2010, an increase of 53%, and municipalities in Group 4 had an average HMR of 8.68, an increase of 3.33%. Again, in the mid-1990s, homicide trajectories in Group 6 diverge, increasing dramatically by 207% to 42.49 in 2010. Table 3 shows that Group 6 municipalities tend to have larger populations and score higher on
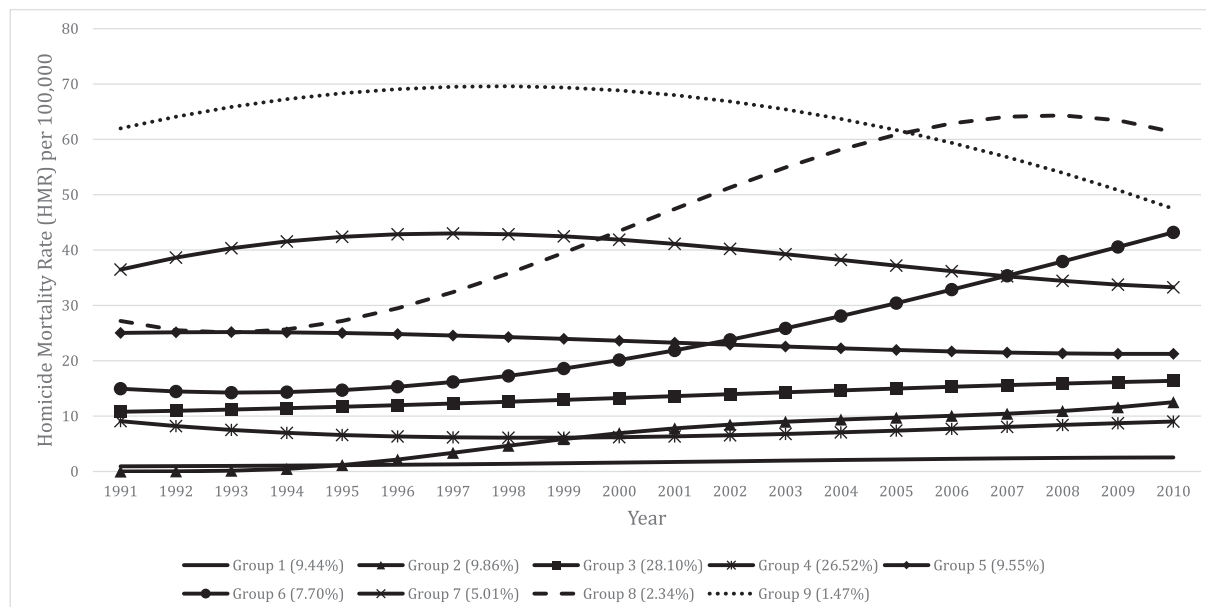
Fig. 1. Predicted group trajectories of homicide mortality rates for Brazilian municipalities (n = 4490).

Table 3
Descriptive statistics for homicide mortality rate trajectory groups.

Trajectory group	N (%)	Homicide Mortality Rate 1991	Homicide Mortality Rate 2010	Population 1991	Social disorganization score 1991
		Mean (Std)	Mean (Std)	Mean (Std)	Mean (Std)
Group 1: Low HMR, stable trajectory	424 (9.44)	1.24 (3.95)	2.89 (5.95)	6390 (4987)	−0.02 (0.99)
Group 2: Low HMR, increasing trajectory	443 (9.86)	0.00 (0.00)	12.42 (11.59)	8855 (6613)	0.42 (0.97)
Group 3: Medium HMR, small increasing trajectory	1262 (28.10)	10.88 (8.71)	16.61 (9.87)	26662 (39222)	−0.06 (0.99)
Group 4: Medium HMR, stable trajectory	1191 (26.52)	8.40 (9.02)	8.68 (7.92)	15520 (19785)	−0.09 (1.05)
Group 5: Medium/high HMR, decreasing trajectory	429 (9.55)	25.46 (14.24)	21.69 (10.57)	44634 (123181)	−0.25 (0.89)
Group 6: Medium HMR, high increasing trajectory	346 (7.70)	13.84 (10.74)	42.49 (14.88)	59415 (210655)	0.39 (0.88)
Group 7: Medium/high HMR, peak and decreasing trajectory	225 (5.01)	36.97 (18.49)	34.04 (15.70)	143022 (745078)	−0.10 (0.98)
Group 8: Medium/high HMR, high increasing trajectory	105 (2.34)	26.13 (16.08)	62.22 (20.86)	55490 (83689)	0.27 (0.69)
Group 9: High HMR, peak and decreasing trajectory	66 (1.47)	63.51 (27.79)	47.26 (20.43)	157011 (242272)	−0.38 (0.82)
N	4491	4490	4490	4490	4406

Note. Std = Standard deviation.

SD.

Municipalities in Groups 5 and 8 had on average very similar HMR in 1991: 25.46 and 26.13. However, Group 8 experienced a 138% increase in HMR until 2010, whereas Group 5 experienced a 14.8% decrease in the same period. Similar to previous descriptive findings, Group 8 municipalities have on average higher SD scores in 1991.

Finally, we compared the three trajectory groups that contained municipalities with the highest homicide levels in 1991. Groups 7, 8, and 9 comprise 5.01%, 2.34%, and 1.47% of included municipalities, respectively (Table 3). Groups 7 and 9 have differing average HMR in 1991 (36.97 and 63.51). However, both groups experienced similar shaped trajectories. HMR in these groups peaked in the late 1990's before declining to levels lower than 1991. Between 1991 and 2010, Groups 7 and 9 saw a 7.9% and 25.6% decrease, respectively. By contrast, Group 8 started at similarly medium-high HMR levels but saw a dramatic increase over the same period. Group 8 has on average higher levels of SD than Group 7 and 9. It should be noted that Group 5 also presented high HMR in 1991 and a similar shaped trajectory to those found for Groups 7 and 9. Additionally, Groups 5 and 8 begin with similar levels of HMR but evolve into clearly divergent trajectories. Since our main interest is to investigate factors associated with distinct trajectories we chose to compare Group 5 with Group 8 in a distinct model, instead of comparing Groups 5, 7, 8, and 9.

Based on the nine trajectories that were identified, we devised four comparisons (Models 1 through 4). In Model 1, Group 1 (low HMR, stable trajectory) is compared with Group 2 (low HMR, increasing trajectory); in Model 2, Group 5 (medium/high HMR, decreasing trajectory) is compared with Group 8 (medium/high HMR, increasing trajectory); in Model 3, Group 4 (medium HMR, stable trajectory) is compared with Group 3 (medium HMR, small increasing trajectory) and Group 6 (medium HMR, high increasing trajectory); and in Model 4, Group 7 (medium/high HMR, peak and decreasing trajectory) is compared with Group 9 (high HMR, peak and decreasing trajectory) and Group 8 (medium/high HMR, high increasing trajectory). Models 1 and 2 are estimated using LR techniques, and Models 3 and 4 are estimated using MLR regression techniques.

Model 1 in Table 4 shows that municipalities with high SD (OR = 2.02, 95% CI: 1.40−2.93) are significantly more likely to experience an increasing HMR trajectory compared to municipalities with low SD. Model 2 shows comparable results.

Model 3 in Table 5 presents the LR results comparing

Table 4
Logistic regression for experiencing and increasing homicide mortality rate trajectory.

Variables		Model 1	Model 2
		Low HMR, increasing trajectory (Group 2)	Medium/high HMR, increasing trajectory (Group 8)
		Ref: Low HMR, stable trajectory(Group 1)	Ref: Medium/high HMR, decreasing trajectory(Group 5)
		OR	OR
		(95% CI)	(95% CI)
Social disorganization score (Ref: Low)	Medium	1.35	3.86***
		(0.94–1.95)	(1.92–7.76)
	High	2.02***	6.67***
		(1.40–2.93)	(3.18–13.99)
Population 1991		1.00***	1.00***
		(1.00–1.00)	(1.00–1.00)
Constant		0.47***	0.07***
N		785	525
Group comparison		Group 1 (Ref) vs. Group 2	Group 5 (Ref) vs. Group 8

Notes. OR = Odds Ratio; CI = Confidence Interval; *** p < .001.

Table 5
Multinomial logistic regression for experiencing an increasing homicide mortality rate trajectory.

		Model 3		Model 4	
		Medium HMR, small increasing trajectory (Group 3)	Medium HMR, high increasing trajectory (Group 6)	High HMR, peak and decreasing trajectory (Group 9)	Medium/high HMR, high increasing trajectory (Group 8)
		Ref: Medium HMR, stable trajectory (Group 4)		Ref: Medium/high HMR, peak and decreasing trajectory (Group 7)	
		RRR	RRR	RRR	RRR
		(95% CI)	(95% CI)	(95% CI)	(95% CI)
Social disorganization score (Ref: Low)	Medium	1.73***	6.06***	0.71	2.31*
		(1.41–2.12)	(4.13–8.88)	(0.35–1.44)	(1.14–4.69)
	High	1.34***	5.52***	0.09***	3.31***
		(1.18–1.76)	(3.79–8.02)	(0.03–0.32)	(1.56–7.02)
Population 1991		1.00***	1.00***	1.00	1.00
		(1.00–1.00)	(1.00–1.00)	(1.00–1.00)	(1.00–1.00)
Homicide rate 1991				1.06***	0.96***
				(1.04–1.08)	(0.94–0.98)
Constant		0.53***	0.04***	0.03***	0.79
N		2724		395	
Group comparison		Group 4 (Ref) vs. Group 3 vs. Group 6		Group 7 (Ref) vs. Group 9 vs. Group 8	

Notes. RRR = Relative Risk Ratio; CI = Confidence Interval; *** p < .001.

municipalities with medium levels of HMR in 1991 and diverging trajectories. Municipalities with both medium and high levels of SD in 1991 were significantly more likely to experience an increasing trajectory compared to those with low levels of SD. Municipalities with high levels of SD are 5.52 times (95% CI: 3.79–8.02) more likely to experience a high increase in HMR.

Model 4 in Table 5 compares the three groups with the highest average municipal HMR in Brazil using MLR techniques. Municipalities with higher levels of SD are significantly less likely to be assigned to Group 9 (RRR = 0.09, 95% CI: 0.03–0.32). It is important to note that groups 7 and 9 have similar trajectory shapes, starting with an increase followed by a peak in the late 1990s, before decreasing to HMR levels lower than in 1991. High levels of SD were associated with significantly higher likelihood of municipalities experiencing a high increasing trajectory (RRR = 3.31, 95% CI: 1.56–7.02) compared to a peak and decreasing trajectory (Group 8 assignment).

Predicted probabilities are reported in Table 6. The estimated probability of a high socially disorganized municipality experiencing an increasing HMR trajectory compared to a stable or decreasing trajectory ranges from 0.18 (Group 6) to 0.52 (Group 2). In most cases, the estimated probability of experiencing an

increasing HMR trajectory compared to respective stable or decreasing trajectories increases from low levels of SD to high levels. For example, the predicted probability of municipalities with medium levels of HMR experiencing an increasing trajectory (i.e. Group 8 assignment vs. Group 5) increases from low (0.07) SD to high (0.33).

4. Discussion and conclusion

The current study makes two contributions to the understanding of temporal variations in municipal level HMR in a developing country. First, we find significant heterogeneity in trajectories, supporting the notion that municipalities as well as individuals can have distinct criminal 'careers' (Bursik and Grasmick, 1992). We identified nine discrete groups of Brazilian municipalities experiencing a range of homicide trajectories, with groups experiencing absolute increases in HMR ranging from 3.33% to 207% between 1991 and 2010, and others experiencing decreasing HMR, with changes ranging from 7.9% to 25.6%. Homicide trajectories showed divergent stable, increasing, and decreasing temporal trends. This is in contrast to the homogeneous patterns found among US cities (McDowall and Loftin, 2009; McCall et al., 2011), which the authors

Table 6
Predicted probabilities for experiencing an increasing homicide mortality rate trajectory.

	Social disorganization score		
	Low	Medium	High
Ref: Low HMR, stable trajectory (Group 1)			
Low HMR, increasing trajectory (Group 2)	0.36	0.43	0.52
	(0.28−0.44)	(0.35−0.51)	(0.45−0.60)
Ref: Medium HMR, stable trajectory (Group 4)			
Medium HMR, small increasing trajectory (Group 3)	0.47	0.52	0.46
	(0.44−0.51)	(0.49−0.56)	(0.43−0.50)
Medium HMR, high increasing trajectory (Group 6)	0.04	0.17	0.18
	(0.03−0.06)	(0.15−0.20)	(0.15−0.21)
Ref: Medium/high HMR, decreasing trajectory (Group 5)			
Medium/high HMR, increasing trajectory (Group 8)	0.07	0.22	0.33
	(0.03−0.11)	(0.17−0.28)	(0.25−0.42)
Ref: Medium/high HMR, peak and decreasing trajectory (Group 7)			
High HMR, peak and decreasing trajectory (Group 9)	0.19	0.13	0.02
	(0.12−0.27)	(0.07−0.18)	(−0.002−0.04)
Medium/high HMR, high increasing trajectory (Group 8)	0.11	0.24	0.34
	(0.05−0.17)	(0.16−0.31)	(0.24−0.44)

Notes. Predicted probabilities are calculated holding all other variables at their means. 95% confidence intervals are reported in parentheses.

argue supports the hypothesis that changes in HMR are influenced by common structural forces (McCall et al., 2011). Our results, in turn, support the hypothesis that in Brazil local municipal-level homicide trends are influenced by local socio-economic and structural forces.

In addition, a small proportion of municipalities (Groups 6–9, 16.52% of included municipalities) accounted for 73.4% of all homicides over the time period, suggesting that lethal violence is spatially concentrated in 'hot spots' (Messner et al., 1999). Thus the steady rise in Brazil's overall HMR since the early 1990's has been primarily driven by a small number of municipalities.

Second, our findings support previous cross-sectional literature linking SD and violence in Brazil (Cardia et al., 2003; Silva, 2014; Duarte et al., 2012; Pereira et al., 2015; Villarreal and Silva, 2006) as well as other countries (Kubrin and Weitzer, 2003; Sampson et al., 1997). This study, however, advances knowledge beyond cross-sectional findings by demonstrating a strong and consistent link between initial SD and increasing HMR. This result is in line with US results in regards to intra-urban areas (Stults, 2010) and large cities (McCall et al., 2011).

The theoretical connection between SD and increasing HMR in high violence, low income countries, is not clearly established. Two pathways are plausible and to some extent intertwined. The first is based on the assumption that SD compromise social capital, community efficacy and, ultimately, informal social control mechanisms, increasing crime and violence (Sampson et al., 1997; Kawachi et al., 1999). Based on these studies, it seems plausible that highly socially disorganized cities are at higher risk for increasing crime and violence, especially if SD is sustained over time.

The second theoretical pathway linking SD to crime and violence is based on the presupposition that SD is connected to the lack of formal social control such as security services and good policing, resulting in a security gap, police violence and misconduct (Kubrin and Weitzer, 2003; Nivette, 2014). A possible consequence of this unstable scenario is the use of extra-legal mechanisms to seek justice and revenge. In a study conducted in São Paulo, Brazil, Peres et al. (2008) found a positive association between deaths from police violence and HMR in the 96 administrative districts of the municipality. Additionally in São Paulo, researchers have found a correlation between social disadvantage and serious human rights violations such as lynching, death by execution, and police violence (Ruotti et al., 2009). The lack of formal social control mechanisms can give rise to the use of violence as a legitimate

means to solve conflicts both individually and through the emergence of organized criminal groups. Violence in modern societies has been linked to insufficient or unequal protection provided by the state (Anderson, 1999; Eisner, 2009; Nivette, 2016). Vigilante groups and youth gangs also flourish within weak and corrupt states (Rotberg, 2004).

Our results have some implications both for policy and future research: first, the association between high SD and increasing trajectories supports the idea that investments in social policies that attend to social disadvantages such as poverty, lack of education, and poor living conditions would also reduce homicide mortality over time; second, the finding that highly violent and highly socially disorganized municipalities have also experienced declining homicide rates suggests that in these contexts other social, economic or policy factors are influencing homicide trajectories, such as crime control policies and/or violence prevention measures. It is also possible that these municipalities have invested in public policies to ameliorate the socioeconomic and demographic conditions (Peres et al., 2012), which, in turn effectively reduced homicide rates. In addition, we found that more than 70% of all homicide deaths are concentrated in only 16% of the municipalities in Brazil. The spatial inequality of violence in these "hot spots," could be used as a guide to establish policymaking priorities and to allocate resources aiming to control and prevent lethal interpersonal violence. Following this recommendation, policymakers should examine more closely the "successful" municipalities that presented high increasing HMR in 1991, with a peak and subsequent declining homicide trajectory, such as those from groups 7 and 9.

4.1. Limitations

Our study has several limitations. First, we excluded the municipalities created after year 1991 (n = 1401). Excluded municipalities were systematically different in regards to HMR and socioeconomic indicators. Specifically, all excluded municipalities had at least one homicide in the period, lower HMR and poorer socioeconomic conditions. Our results are therefore biased towards larger, more socio-economically advanced municipalities. In addition, the exclusion of new municipalities could bias our results because doing this, we excluded areas and populations that were previously part of some of the municipalities included in our study, what could result in an overestimation of the HMR. However, once homicide count would also be affected by the exclusion, this could

to some extent offset the overestimation of the HMR.

Importantly, the possible overestimation of HMR would not be avoided if we chose to work with all municipalities: changes in population size and homicide count would affect both original and new municipalities. One way to deal with this would be to keep the borders stable over time so that population and homicide count would refer to the same spatial area during the whole period. Unfortunately, we do not have access to the cartographical base for different periods to make this possible. Furthermore, the inclusion of newly created municipalities would introduce the additional problem of interrupted time series. Thus to avoid these issues, we limited our sample to the Municipalities that exist throughout the whole historical series. It is important to mention again that our results are consistent with previous studies showing that SD is associated with high or increasing homicide trajectories.

Second, the misclassification of homicide death may result in an underestimation of HMR. To deal with this we reclassified death due to undetermined intention in an effort to minimize misclassification bias. Third, we focus exclusively on SD whereas other variables may be important to explain homicide trajectories, such as cultural norms (Corzine et al., 1999) and crime control variables (Parker et al., 2016). However, information on these potential factors is limited, and so we could not investigate these characteristics in the current study.

Fourth, we examined relative comparison groups separately to ensure that similar groups were being compared and for ease of interpretation and presentation given the large number of groups. However, we acknowledge that examining each comparison group separately may have increased the likelihood of finding statistically significant results (Long, 1997). A way to deal with this is to apply some correction factor such as Bonferroni's. The application of Bonferroni's correction factor results in a more conservative significance level to test individual hypotheses. It takes into concern the number of hypotheses tested, in our case 12 (2 in Model 1, 2 in Model 2, 4 in Model 3, and 4 in Model 4). Applying Bonferroni's correction, our alpha to reject the null hypothesis would be $0.05/12 = 0.00417$, thus not changing our main conclusions.

Finally, we did not consider temporal variation of SD. As such, we are not able to assess the impact of changing SD levels on homicide over time, which would illuminate the possible causal connection between SD and homicide. However, Stults (2010) examined the effects of both initial SD and changes in SD over time on homicide in Chicago and found that, for some group comparisons (i.e. high increasing vs. decreasing), initial SD was associated with group membership but changes in SD were not. In this case, it is possible that the negative effects of SD on social networks have long-term effects, even after a reduction in SD, since it interferes with complex social process and informal and formal social control mechanisms such as cohesiveness, social efficacy, social capital, consolidation of organized crime groups and illegal use of violence as a means to solve conflicts (Sampson et al., 1997). It is also plausible that in highly violent areas, the reduction of SD alone is insufficient to decrease homicide levels. In addition to investment in social policies, policymakers must take measures to reduce crime and violence through security and prevention policies.

5. Conclusion

In summary, our results highlight the spatial and temporal heterogeneity of homicide mortality in Brazilian municipalities. While national trends are steadily increasing, disaggregating municipal trajectories shows that this is driven by a small proportion of municipalities in the country. We found that SD is associated with an increasing homicide trajectory. This result generally supports the notion that poor social structural conditions can create "space" for criminal behavior and groups and, consequently, violent death. Two theoretical pathways are possible: (1) SD weakens a community's capacity for informal social control (i.e. collective efficacy and social capital) and/or (2) SD is connected to a security gap, increasing the use of extra-legal mechanisms to seek justice and revenge. Both pathways would result in higher levels of crime and violence. Future research should closely examine the effects of SD on these mediating mechanisms, including weakened social controls, as well as the security gap and subsequent growth of organized criminal groups and associated violence.

Appendix

Appendix Table 1
Characteristics of included and excluded Brazilian municipalities (2010)

	Mean	Std	Median	IQR	p-value
Age-standard homicide mortality rate (2010)					
Included	17.68	19.44	13.05	0–26.21	<0.001
Excluded	15.52	22.04	0	0–26.45	
Population (2010)					
Included	40334.2	225465.100	13646	6591–27466	<0.001
Excluded	8952.43	20267.44	4894	3018–8553	
Illiteracy among those 15 years or older (%) (2010)					
Included	15.85	9.71	12.81	7.89–23.99	<0.001
Excluded	17.45	10.26	14.55	9.42–25.52	
Unemployment (2010)					
Included	6.49	3.53	6	4.06–8.2	<0.001
Excluded	5.72	4.15	4.98	2.68–7.76	
Water supply (%) (2010)					
Included	86.09	13.89	90.58	79.87–96.53	<0.001
Excluded	83.53	17.62	89.21	78.55–95.02	
Electricity supply (%) (2010)					
Included	97.56	5.2	99.45	97.99–99.88	<0.001
Excluded	95.61	8.47	99	95.66–99.79	
Urban population (%) (2010)					
Included	67.24	20.42	68.67	51.52–84.46	<0.001
Excluded	49.51	22.78	46.59	30.78–65.23	
Gini Index (2010)					
Included	0.5	0.06	0.49	0.45–0.54	0.07
Excluded	0.49	0.07	0.49	0.44–0.54	
Houses headed by lower educated women with children (%) (2010)					
Included	19.72	9.74	18	12.45–25.42	0.19
Excluded	20.96	12.39	18.91	11.8–28.21	
Infant mortality rate (2010)					
Included	19.02	6.95	16.7	13.70–23.60	<0.001
Excluded	20.18	7.79	17.7	14.30–24.90	
Poverty (% income less than R$ 140,000/month) (2010)					
Included	22.34	17.6	16.56	6.62–37.68	<0.001
Excluded	26.86	18.73	23.61	10.16–42.01	
Per capita income (2010)					
Included	506.78	246.86	486.69	287.45–666.73	<0.001
Excluded	438.49	219.28	404.27	256.27–575.08	

Notes. Std = Standard deviation. IQR = Interquartile range.

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