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Virus containment measures and homicide in Mexico: An assessment of community strain theory

Carlos Vilalta [a,*], Gustavo Fondevila [b], Ricardo Massa [b]

[a] Center for Research in Geospatial Information Sciences (CentroGeo), Contoy 137, Lomas de Padierna, 14240 Ciudad de México, Mexico
[b] Center for Economic Research and Education (CIDE), Carr. México-Toluca 3655, Santa Fe, 01210 Ciudad de Mexico, Mexico

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ABSTRACT

Objectives: This study examined whether Covid-19 virus containment measures moderated the relationship between community strain and homicide rates in Mexico City neighborhoods and police quadrants.
Methods: We tested the moderation effects hypothesis with the use of a mixed-effects regression to estimate fixed effects with random effects at different levels of aggregation. A sensitivity analysis was used to assess whether results of the moderation effects were affected by changes in the unit of analysis.
Results: We found no evidence that virus containment measures moderated the relationship between community strain and observed changes in homicide rates. Moreover, although community strain measures were found to be statistically associated with homicide rates, the results were seemingly affected by the Modifiable areal unit problem (MAUP).
Conclusions: First, the link being made in the literature between the homicide drop and the Covid-19 pandemic based on strain theory premises has no universal empirical basis. Second, although homicide rates dropped on average after containment measures were implemented, these had different effects across places, making arguments based on overall average change inexact. Third, we find evidence that community strain can predict homicide rates, but results are sensitive to the MAUP. Thus, community strain explanations of homicide rates may only apply in some areas of cities and conditional on the unit of analysis.

1. Introduction

Three theories mainly have been used to rationalize the observed changes in crime trends observed during the pandemic. These theories are Routine activities, Crime pattern, and Strain theory (Brantingham, Tita, & Mohler, 2021; Campedelli, Aziani, & Favarin, 2021; Campedelli, Favarin, Aziani, & Piquero, 2020; Estévez-Soto, 2021; Kim & Phillips, 2021; Nivette et al., 2021). Empirical evidence of these deductions, however, has yet to be provided.

We would agree, on logical grounds, that according to General Strain theory (GST),

the pandemic and virus containment measures must have increased frustration and anger leading to an increase in criminal motivations (Campedelli et al., 2020; Nivette et al., 2021). In places like Mexico City, the stress produced by the rapid worsening of economic conditions AND limited access to public medical services must have greatly increased anger and frustration, perhaps sufficiently enough to lead to homicidal violence in structurally strained communities (Campedelli & D'Orsogna, 2021). However, homicides in Mexico City decreased by 20% after the enactment of the virus containment measures.[1] Of course, it can be the case that homicides associated with strain may have either increased or remained the same during the pandemic at the expense of other motives. It must be considered that many homicides in Mexico City have been linked to organized crime activity (Vilalta, Lopez-Ramirez, & Fondevila, 2021a, 2021b). In fact, one study in Mexico City reports that stay-at-home policies against the Covid-19 virus have had no noticeable effect on organized crime activity (Balmori de la Miyar, Hoehn-Velasco, & Silverio-Murillo, 2021). The key issue here is that we do not know what explains this sudden drop in homicidal violence. Even more, we do not know whether this drop can be associated to the implementation of the virus containment measures, especially when the negative effects of the latter are expected to have increased anger and frustration substantially

* Corresponding author.
E-mail addresses: cvilalta@centrogeo.edu.mx (C. Vilalta), gustavo.fondevila@cide.edu (G. Fondevila), ricardo.massa@cide.edu (R. Massa).

[1] The COVID-19 national emergency was declared in Mexico on March 30th of 2020, and a set of virus containment measures promoting social distancing behaviors were declared to go effective the next day.

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across the city.

Acknowledging the capacity of Macro-level Strain theory (MST) to explain community difference in crime rates in Mexico City (Vilalta et al., 2021a), in this study we test whether containment measures have moderated the relationship between structural strain and homicide at different spatial units of analysis. Our case study is Mexico City and our two spatial units of analysis are the neighborhood and the police quadrant. We examine the previous relationship for the time period between April 2020 to May 2021, that is for the fifteen months in total into the pandemic outbreak in Mexico City, as compared to the previous fifteen months total without the pandemic, that is, between January of 2019 and March 2020. Our focus is on homicide crimes as they were seemingly barely affected by the pandemic in contrast with other crimes in Mexico City and other Latin American cities such as Lima, Peru, Cali, Colombia, and Rio de Janeiro in Brazil (Nivette et al., 2021; Vilalta, Fondevila, & Massa, 2022).

A moderation effects test is the first most basic piece of evidence for demonstrating an effect of the pandemic and virus containment measures on homicide change. In this study we look to fill this gap in previous studies. However, because Macro-level Strain theory (MST) is an environmental criminology theory, we also examine whether its testing is sensitive to the Modifiable area unit problem (MAUP). The MAUP is the problem of finding "Variations in the size of the correlation… conditioned upon changes in the size of the unit used…" (Gehlke & Biehl, 1934). The basic implication of MAUP is that the validity and reliability of statistical analyses based on geographically aggregated data can be put into question. For this reason, we conduct a sensitivity analysis of the previous results at the neighborhood level with the use of police quadrant data, which is another type of unit of analysis for which MST arguments should also apply given quadrant's functional role for controlling crime. Furthermore, since homicide data are longitudinally clustered in neighborhoods and police quadrants, nested within municipalities and police sectors respectively, we employ a set of growth mixed effects models whereby homicide rates are regressed on time, that is the variable reflecting the time period before and after virus containment measures were implemented, structural strain measures, and the interaction of time with each strain measure. These interaction terms are the moderating variables in our moderation tests. As previously said, results of neighborhood analyses are compared to results of police quadrant analyses to assess the MAUP.

In this sense, we make three contributions to the current scholarly literature. First, we provide an absence of evidence of a moderating effect of virus containment measures on the relationship between community strain and homicide rates, both at the neighborhood level and at the police quadrant level of aggregation. What this means is that the link between the homicide drop and the Covid-19 pandemic that is being made on strain theory-based premises has no empirical basis. The geography of homicide can be linked to MST, but the drop observed during the pandemic cannot be linked to structural strain. Second, we provide evidence of significant variability in the effect of the implementation of the containment measures across different units of analysis. What this means is that although homicide rates dropped on average after the containment measures were implemented, these measures had different effects across places, making arguments based on overall average change inexact. Third and final, although we provide empirical evidence to support MST predictions regarding homicide, we also provide evidence that results are sensitive to the MAUP. Thus, we warn other researchers that the sign and magnitude of MST correlations with homicide may vary across units of analysis. MST explanations of homicide rates may only apply in some areas of cities and conditional on the unit of analysis.

2. What is community strain?

General Strain theory (GST) makes the argument that strains increase the prospects of anger and frustration to create pressure for corrective action with crime as potential response (Agnew, 2001; Agnew & Brezina, 2019; Pratt & Godsey, 2003). GST asserts that varying levels of anger and frustration moderate the effects of strain on crime. Strain refers to "relationships in which others are not treating the individual as he or she would like to be treated" (Agnew, 1992: p. 48; Agnew, 2001). Anger and frustration together increase the odds of retaliation by energizing action and lowering inhibition, thus making crime a likely reaction to negative emotions (Agnew, 1992, 2011). Strain is most likely to lead to crime if there is a combination of the five following factors: lack of skills and resources to cope with strain lawfully, low social support, low social control, blaming of others, and disposition to crime (Agnew, 2001).

In 1999, Agnew extended GST to explain community differences in crime rates. He presented a diagrammatic conceptualization and operationalization of GST at the community level (see Fig. 1). Previous studies have called this extension of GST to the community level as Macro-level Strain theory (MST) (Agnew & Brezina, 2019; Botchkovar, Antonaccio, & Hughes, 2018; Brezina, Piquero, & Bellair, 2001; de Beeck, Pauwels, & Put, 2012a; Vilalta et al., 2021a; Warner & Fowler, 2003). By "community", Agnew (1999) meant any type of settlement area, though he suggested that the theory would be "better tested with data from smaller areas" as they are more homogeneous (p. 124). MST studies have applied this definition of community to different types of units of analysis such as countries (Rennó Santos, Testa, & Weiss, 2018), neighborhoods (Botchkovar et al., 2018; Warner & Fowler, 2003), schools (de Beeck et al., 2012a; de Beeck, Pauwels, & Put, 2012b; Brezina et al., 2001), or census information units (Wareham, Cochran, Dembo, & Sellers, 2005). We currently lack a thorough discussion on what type of unit of analysis is better suited to represent the "community" in MST terms, and what spatial unit of information (e.g., census block, census tract, neighborhood, police quadrant, etc.) best represents such unit of analysis in urban contexts (Vilalta, 2013).

In MST terms, the characteristics of strained communities are economic deprivation, inequality, population size, density and overcrowding, high population mobility, and high non-white population. These socioeconomic and sociodemographic characteristics operate to create strain through a variety of intervening mechanisms.

Previous characteristics are conceptually based on social disorganization theory reinterpretations and extensions, as well as on relative deprivation and subcultural deviance theories. MST builds upon previous theories to explain that community differences in crime are a function of economic and noneconomic variables. The difference of MST with previous theories is that individuals are pressured into delinquency by their circumstances, where individual strain is not disconnected from social context. Rather, coping behaviors are intervening mechanisms by which strained communities affect individual levels of strain and disposition to crime. In this sense, the intervening mechanisms in MST are the selection and retention of strained individuals, goal blockage, relative deprivation, loss of positive stimuli, the presentation of negative stimuli, and interaction with angry and frustrated people. In sum, MST builds upon GST by claiming that community differences in crime are a function of community differences in lack of skills and resources to cope with strain, low social support, low social control, and disposition to crime (Agnew, 1999, 2001).

More in detail, economically deprived communities are expected to have higher levels of crime and violence as they are more likely to select and retain economically strained individuals (Agnew, 1999; Wareham et al., 2005). The idea that economic deprivation and inequality lead to emotions of anger and frustration, the blame of others, and eventually to crime, including homicide (Blau & Blau, 1982; Messner, 1982; Pratt & Godsey, 2003), was borrowed from social disorganization theory and the relative deprivation view in criminology and sociology respectively. MST argues that economic deprivation and inequality amplify the sense of powerlessness, mistrust, prejudice, and competition among individuals and groups in the community. Likewise, it is also argued that strained individuals have financial limitations to move out from strained

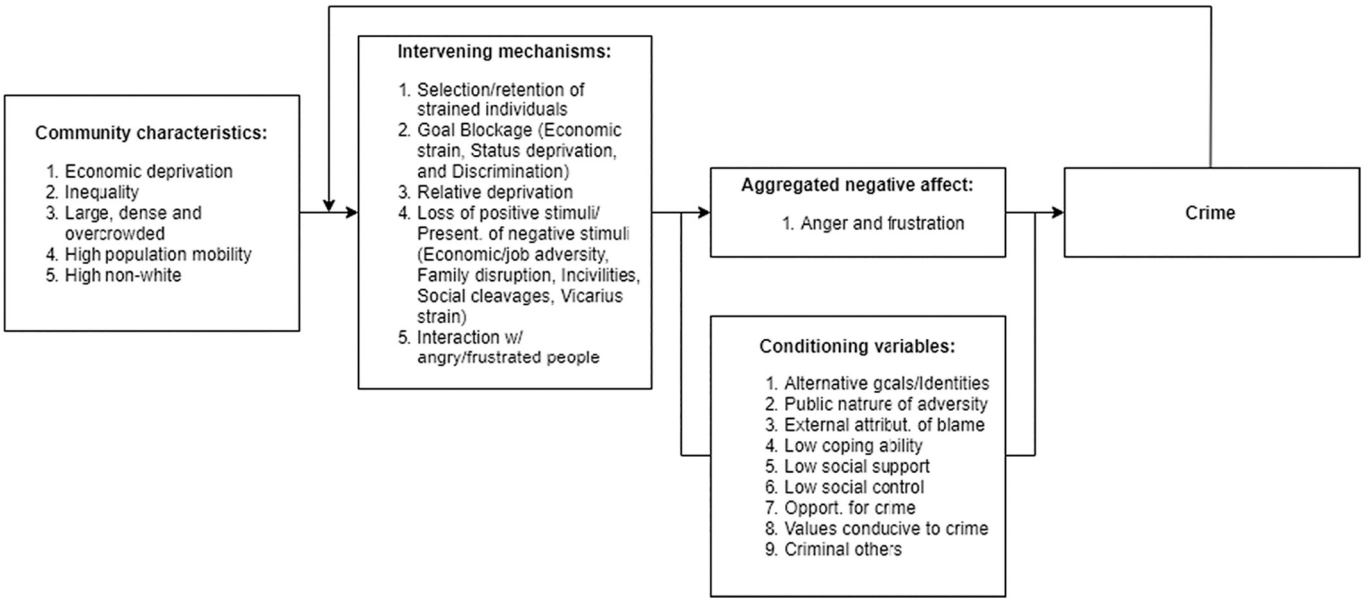


Fig. 1. A General Strain Theory of community differences in crime.
Source: Agnew, 1999

communities, while at the same time, strained communities have less capacity to resist the entry of strained individuals (Agnew, 1999).

Another part of the MST argument is that localized economic deprivation and inequality cause goal blockage, the latter causing local negative environments conducive to crime (Agnew, 1992, 1999). For GST, the causal mechanism is that crime is one alternative among dissatisfied individuals to overcome the failure to achieve socially expected goals or to reduce their expectations-achievement gap (Agnew, 1992). MST thus explains that residents in strained communities have lower chances of achieving positively valued goals as they face more economic/job adversity, negative stimuli, family disruption, incivilities, and interactions with angry/frustrated people (see Fig. 1). In addition, given the concentration of strained individuals in strained communities, these individuals have higher chances of interacting with each other thus increasing the likelihood of negative interaction and conflict with one another (Wareham et al., 2005).

A variety of concentrated disadvantage measures have been used in the MST literature as a proxy for community economic deprivation and inequality (Botchkovar et al., 2018; Fagan, Wright, & Pinchevsky, 2014; Vilalta et al., 2021a; Wareham et al., 2005; Warner & Fowler, 2003). Concentrated disadvantage is a major concept and empirical correlate used in social disorganization and collective efficacy tests (Gerstner, Wickes, & Oberwittler, 2019; Graif & Sampson, 2009; Vilalta & Muggah, 2016). The argument in favor of using concentrated disadvantage measures to represent social disorganization is that the former is a tangible indicator of the likelihood of residents to take an active role in crime prevention (Sampson, Raudenbush, & Earls, 1997). Previous tests of MST confirm there is a positive correlation between concentrated disadvantage with delinquency and violence (Vilalta et al., 2021a; Wareham et al., 2005; Warner & Fowler, 2003). Others find no evidence of such correlation however (Botchkovar et al., 2018; Fagan et al., 2014).

MST also borrows from social disorganization theory the argument that dense, overcrowded, and transient communities have less ability to organize and solve common problems such as crime and peer delinquency (Sampson & Groves, 1989). MST goes on to argue that strained communities tend to have large populations and densities, household overcrowding, and higher rates of residential mobility (Agnew, 1999). One previous test of MST does confirm that residential mobility increases community strain and violence (Warner & Fowler, 2003), although another study in Mexico City presents mixed results with regards to population size, population density, household crowding, and residential mobility (Vilalta et al., 2021a). In this sense, MST is not a catch-all theory of crime. Some examples are the following. One study report that strain contextual effects correlate with self-reported measures of violent offending (e.g., physical violence), but not with measures of general offending (e.g., vandalism or minor theft) (de Beeck et al., 2012b). Another study reports that school-aggregated measures of student anger can predict student-to-student aggression but not student-to-teacher aggression (Brezina et al., 2001). One study more concludes that controlling for individual sources of strain, community-level strains are not correlated with self-reported measures of criminal disposition (Botchkovar et al., 2018).

Of course, neither GST nor MST claim that strained individuals will respond to anger and frustration with crime nor that the effect of strain on crime is automatic or immediate (Agnew, 1992, 1999). It must be reminded that Agnew (1992) argued that stressful life events that accumulate over short time spans are consequential to explain criminal behaviors. This argument was in itself based on Linsky and Straus (1986)) macro-social stress theory, which links community-based stressors with individual smoking practices to explain why under conditions of high stress, some people fail to exercise normal prudence. According to them, some examples of stressful consequential life events are divorce, business failures, new unemployment, bankruptcies, mortgage foreclosures, the arrival of new migrants, new welfare recipients, high-school dropouts, and natural disasters (Linsky & Straus, 1986). The MST argument, to be complete, needs to say that stressors not only cluster spatially, but must accumulate over time, and be highly consequential before negative outcomes like crime arise.[2]

3. The link between virus containment measures and community strain

Covid-19 virus containment measures were implemented to prevent transmission and curtail massive contagion. Measures varied notably across national and subnational governments. The COVID-19 national

[2] Furthermore, the cumulative effect of stressors on crime is most likely interactive rather than simply additive (Agnew, 1992).

emergency was declared in Mexico on March 30th of 2020 with a set of virus containment measures going effective the next day.[3] Virus containment measures consisted on the immediate suspension of non-essential activities, the prohibition of holding meetings of >50 people in so-called essential sectors of the economy (e.g. medical services, public security services, public transport, groceries, energy services, etc.), wash hands, follow respiratory etiquette, keep a healthy distance, stay home as much as possible for anyone under 60 years old and compulsory for anyone over the age of 60 or with diseases that make them vulnerable to the virus, and the postponement of censuses and surveys involving physical interaction.[4] These measures created strain and protest among workers in the informal economy and street vendors, and citizen resistance against checkpoints limiting entrance to some cities, as well as over mark-wearing regulations (Campedelli & D'Orsogna, 2021).

As said in the introduction, some criminologists hold that virus containment measures have changed the social dynamics in which criminal behavior occurs (Boman & Gallupe, 2020), particularly in terms of changes in routine activities, crime patterns, and strains (Brantingham et al., 2021; Campedelli et al., 2020; Campedelli et al., 2021; Estévez-Soto, 2021; Kim & Phillips, 2021; Nivette et al., 2021). According to General Strain theory (GST), the arrival of the pandemic and corresponding virus containment measures must have increased stress, frustration and anger, leading to an increase in criminal motivations (Campedelli et al., 2021; Nivette et al., 2021). The economic impact of the pandemic and containment measures have been estimated in Mexico: An increase of 7.6% in extreme poverty, an increase of 6.3% of the total poverty rate, and >20 million people left without employment, at least momentarily and only during 2020 (Esquivel, 2020). Thus, it seems reasonable to argue that the stress produced by the rapid worsening of economic conditions must have greatly increased anger and frustration, perhaps sufficiently enough to lead to homicidal behavior. However, what we find is that homicide rates in Mexico City actually dropped by 20% between April 2020 when the virus containment measures were implemented and may 2021, although it is reported that they remained stable around municipal averages during the first 10 weeks after the stay-at-home orders were implemented (Balmori de la Miyar et al., 2021).[5] However, specifically with regards to community strain, the expectation is that commitment to legal norms and bonding relationships must have decreased due to the stress caused by economic hardship. In addition, the lack of access to medical services and means to prevent contagion, may have increased anger and frustration towards members of the political class, members of the community, and outsiders. The pandemic was a catastrophic event in which social support systems like hospitals and social policy agencies failed, where prosocial and bonding relationships that are at the core of strain theory, were put to the test. Virus containment measures and the virus itself created massive traumatic events such as the death of loved ones, sudden unemployment, financial losses, evictions, etc. In this sense, the pandemic must have triggered feelings of denial, shock, and disbelief, as well as acute fear, anxiety, and helplessness (Goff, 2021), particularly among frustrated and isolated individuals who had already lost the ability to cope with adversity (Levin & Madfis, 2009).

However, not only homicides decreased significantly since the containment measures were implemented, but we have no evidence of containment measures actually moderating the relationship that has been reported in studies prior to the pandemic between community strain and homicidal violence (Vilalta et al., 2021a). We do not know whether these relationships were modified with the arrival of the pandemic. As such, it might be the case that the observed homicide drop may or not be related to structural community strain. It can be the case that homicides associated to community strain may have either remained the same or even increased during the pandemic at the expense of other motives.

4. Data and methods

4.1. Case study and variables

Our case study is Mexico City and the two units of analysis are the neighborhood ($N = 1824$) and the police quadrant ($N = 847$). The average Mexico City neighborhood is 0.47 km^2 (0.18 $mile^2$) with a mean of 5035 residents according to the 2020 census. In addition to neighborhoods as proxy for communities, we used the police quadrant mainly to assess the MAUP. The police quadrant may also serve as a proxy for community as they are the basic unit for community proximity policing and are at the core of the current citizen policing supervision strategy in Mexico City. The average Mexico City police quadrant is 1.05 km^2 (0.41 $mile^2$) with a mean of 10,771 residents according to the 2020 census.[6] The neighborhood geographic shapefile was obtained from the National Electoral Institute of Mexico and the police quadrant geographic shapefile was obtained from the Open Data Portal of Mexico City.[7]

The dependent variable is the intentional homicide (i.e., murder) rate per 10,000. Homicide data was downloaded from the Open Data office of Mexico City.[8] These data contain the geographic coordinate of the homicide incident (point data). Homicides were aggregated to their corresponding neighborhood and police quadrant (polygon data) and geospatially matched with census data. It must be noted that 9.9% of the 4231 total intentional homicides recorded did not include the coordinates of the incident. As such, a total of 3810 (90.1%) recorded intentional homicides were used in the analysis. Fig. 2 shows the monthly count of homicides for the time periods before and after the virus containment measures were implemented. Table 1 shows the homicide rates by neighborhood and police quadrants as well as the change between periods. Table 2 presents the variables, measures and data sources.

Time is the independent variable representing the time period before the virus containment measures were implemented ($T = 0$) and the time period after ($T = 1$). The Covid-19 national emergency was declared in March 30th of 2020 to begin on April 1st of 2020. We examine the impact of the virus containment measures between April 2020 to May 2021, that is for the fifteen months in total into the pandemic outbreak in Mexico City, as compared to the previous fifteen months total without the pandemic, that is, between January of 2019 and March 2020. For this reason, we have 3648 neighborhood-time Level 1 observations (1824*2) and 1694 police quadrant-time Level-1 observations (847*2).

To represent community economic deprivation and inequality in MST terms, we used Principal Component Analysis (PCA) to create an index measure composed of the male population between 18 and 24 years old (%), population not beneficiary of public medical services (%), and population 15 years old or more with incomplete elementary schooling (%). This index measure has already been used for the same purpose in previous studies in Mexico City, which have been based on MST and Collective efficacy theory premises regarding the measurement of concentrated disadvantage and neighborhood social stratification (;

[3] See: https://dof.gob.mx/nota_detalle.php?codigo=5590914&fecha=31/03/2020

[4] These measures have remained for the most part including December of 2021 when this study was being produced.

[5] Homicide victims reduced from 2121 to 1689 between April 2020 and June 2021 as compared to the previous 15-month period, that is, between January of 2019 and March of 2020.

[6] There are 15,245 inhabitants fewer living in police quadrants than in neighborhoods, although the total area of police quadrants is 889.4 km^2 whereas the total area of neighborhoods is 857.3 km^2.

[7] Visit: https://datos.cdmx.gob.mx/dataset/cuadrantes

[8] Visit: https://datos.cdmx.gob.mx/dataset/victimas-en-carpetas-de-investigacion-fgj

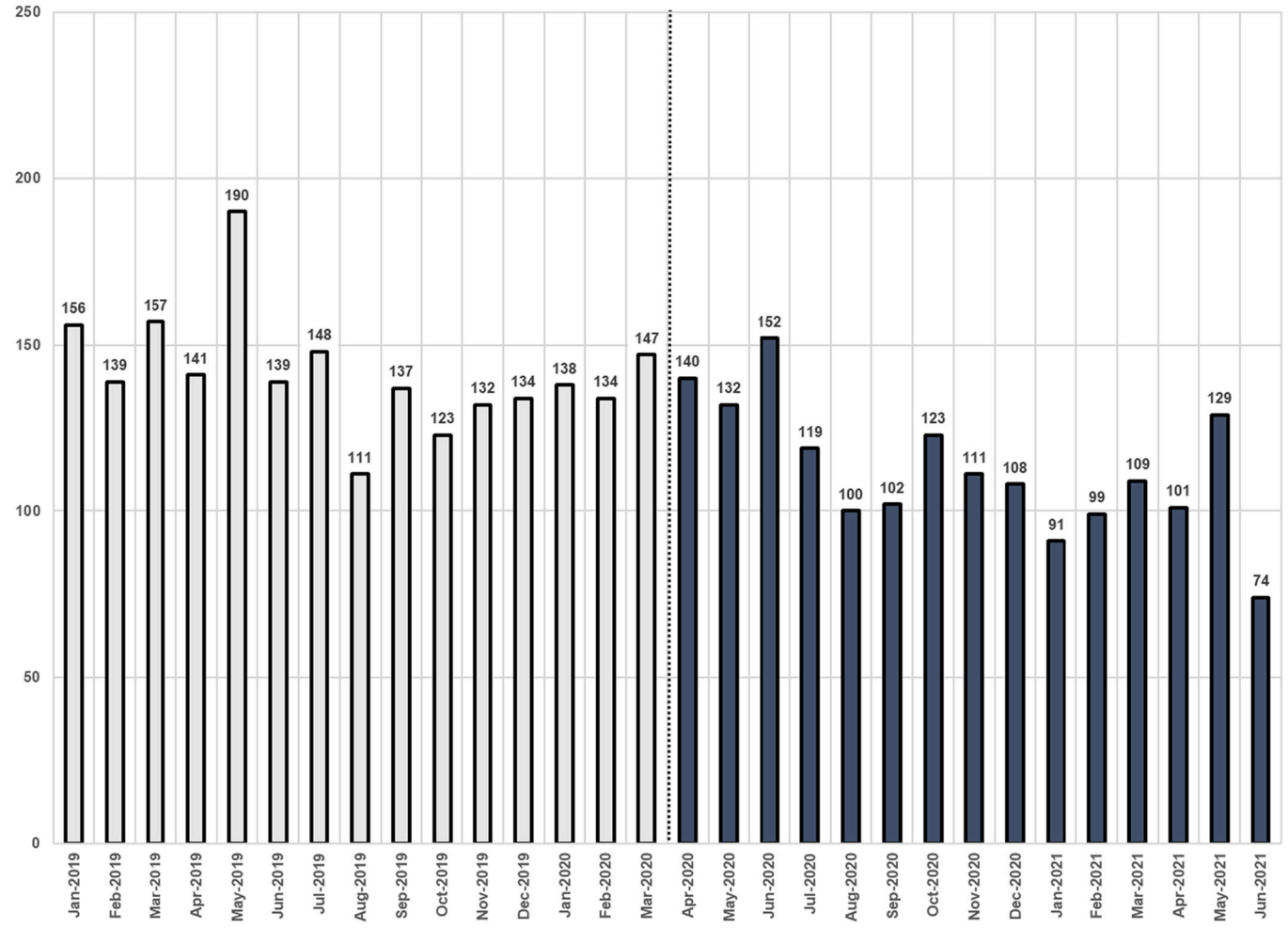


Fig. 2. Mexico City Monthly Count of Homicides Before and After Implementation of Covid-19 Containment Measures.
Data source: Open Data office of Mexico City. Note: The dotted vertical line separates the 15-month periods before and after containment measures were implemented.

Table 1
Homicide rates per neighborhood and police quadrant

	N	Population*	Homicide rate ($T = 0$)**	Homicide rate (T = 1)**	Change
Neighborhoods	1824	9,183,597	2.31	1.84	−20.4%
Police quadrants	847	9,123,236	2.32	1.85	−20.4%
Homicides			2121	1689	−20.4%

* Differences in population are due to the fact that not all population in the city are accounted for by the police quadrants area.
** Homicide rates per 10,000.

Vilalta et al., 2021b). The first component of our PCA index explains 61.8% and 76.0% of the total variation in neighborhoods and police quadrants respectively (See Table A1 in the appendix).[9]

The strain effect of living in dense neighborhoods was represented by population density (population/km^2 x 1000). Crowding was represented by the mean number of persons per bedroom in privately owned homes. Population mobility was represented by the percent of residents living outside Mexico City at least five years prior to the 2020 census. To

Table 2
Variables, measures and data sources

Variable	Measure	Data source
Homicide rates	Intentional homicide rate per 10,000	ADIP, Mexico City
Time	The 15-month time periods before/after containment measures were implemented	Own definition based on available data
Economic deprivation and inequality	PC index measure of the male population between 18 and 24 years old (%), population not beneficiary of public medical services (%), and population 15 years old or more with incomplete elementary schooling (%)	Population census, 2020
Population density	Population by square kilometer x 1000	Population census, 2020
Crowding	Mean number of persons per bedroom in privately owned homes	Population census, 2020
Population mobility	Residents living outside Mexico City at least five years prior to the census (%)	Population census, 2020
Minority population	Five and more year-old native speaking population (%)	Population census, 2020
Organized crime activity	Rate of criminal investigations for drug dealing	ADIP, Mexico City

[9] One reviewer suggested to use these variables separately, however it would multiply the interaction tests complicating the results unnecessarily.

Table 3
Correlation matrix

	Homicide rate	Econ. deprivation	Density	Crowding	Pop. mobility	Indian population
Neighborhoods:						
Homicide rate	1.000					
Econ. deprivation	0.163***	1.000				
Density	−0.070***	0.043***	1.000			
Crowding	0.032	0.409***	−0.025	1.000		
Pop. Mobility	−0.045***	−0.377***	−0.002	−0.269***	1.000	
Indian population	0.073***	0.510***	−0.097***	0.188***	−0.031	1.000
Org. crime activity	0.267***	0.106***	0.021	−0.022	0.021	0.090***
Police quadrants:						
Homicide rate	1.000					
Econ. deprivation	0.100***	1.000				
Density	0.012	0.290***	1.000			
Crowding	−0.012	0.568***	0.142***	1.000		
Pop. mobility	−0.122***	−0.433***	−0.060**	−0.521***	1.000	
Indian population	0.241***	0.292***	0.003	0.329***	−0.121***	1.000
Org. crime activity	0.250***	0.400***	0.356***	0.169***	−0.174***	0.129***

*** $p < 0.01$, ** $p < 0.05$.

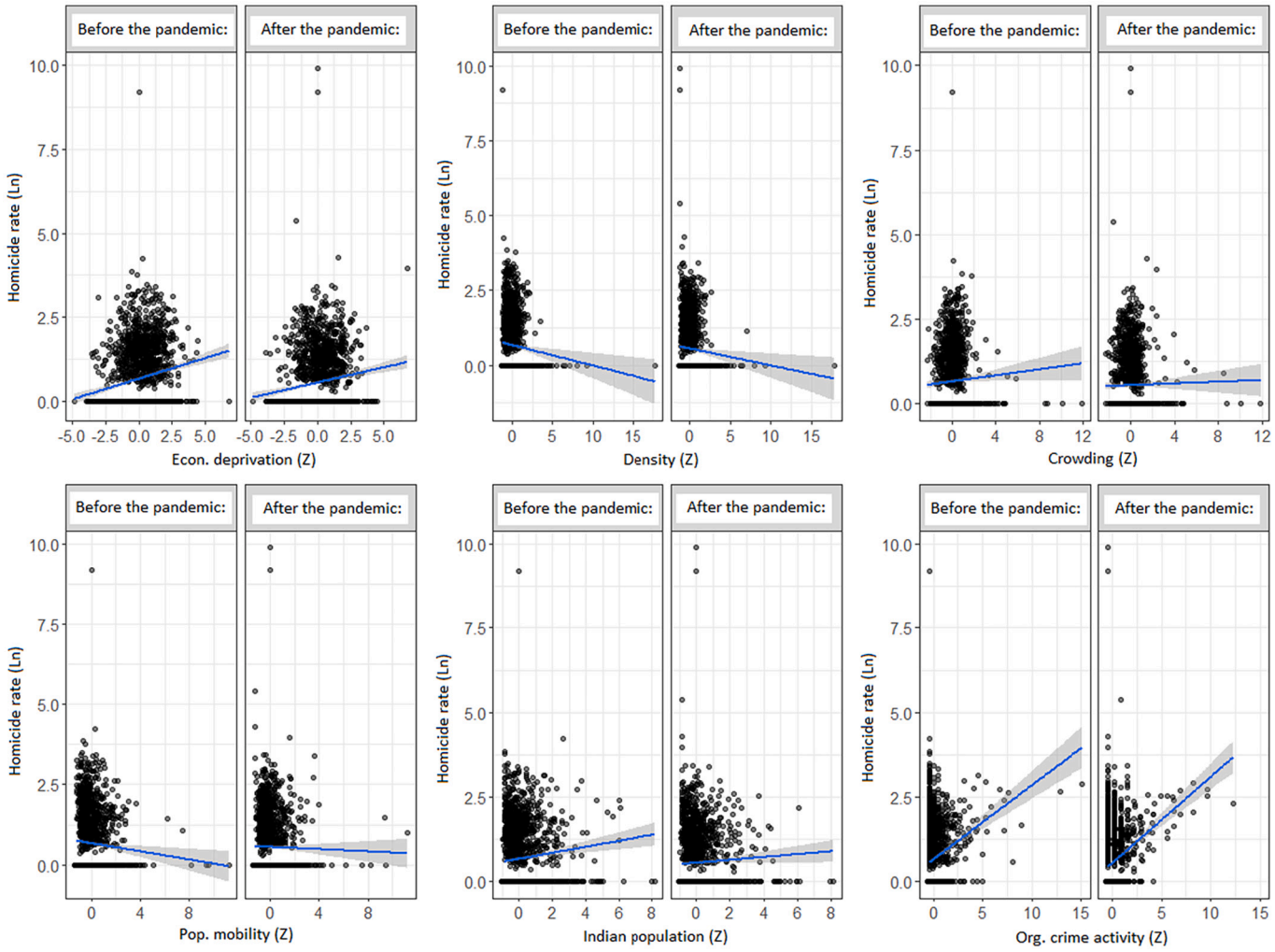


Fig. 3. Interaction plots between homicide rates and strain correlates at the neighborhood level.

represent the minority population, we used percent of five and more years old native speaking resident population in the geographic unit. As previous studies indicate, the Indian-speaking population in Mexico tends to live in poor areas neighborhoods and is more susceptible to suffer from discrimination. These variables were collected at the census block level and were later aggregated at the neighborhood level for our analysis. The source of data is the 2020 population census. Finally, we used the rate (x 1000 neighborhood residents) of criminal investigations for drug dealing (i.e., *narcomenudeo*) as a proxy for organized crime activity. This variable has be utilized in previous studies related to homicide in Mexico City (Vilalta et al., 2021a, 2021b). These data was also downloaded from the Open Data office of Mexico City and was

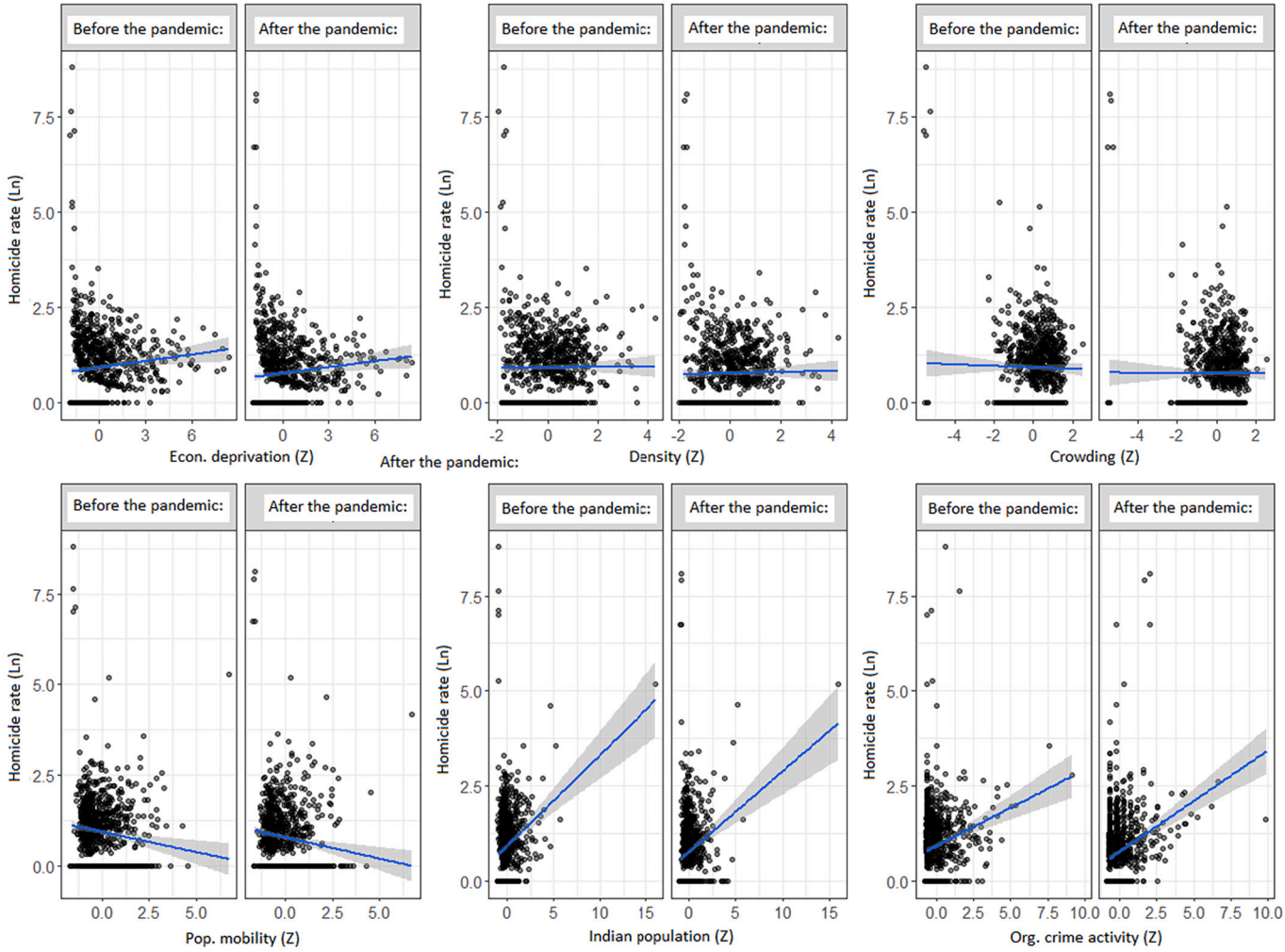


Fig. 4. Interaction plots between homicide rates and strain correlates at the police quadrant level.

aggregated to its respective neighborhood of occurrence.

Prior to multivariate analyses which are explained in the section below, we present a correlation matrix (see Table 3) and interaction plots to visually examine the relationships between homicide rates and the MST correlates in the time periods before and after the pandemic and its corresponding social distancing measures (see Figs. 3 and 4). These interaction plots should be able to insinuate graphically whether there was a possible effect of the containment measures on the relationship between homicide and MST correlates. However, the slopes remain apparently unchanged between time periods, meaning that we are not able to visualize the existence of a moderation effect. However, moderation effects require statistical testing.

4.2. Empirical strategy

We tested the moderation effects hypothesis with the use of a mixed-effects regression to estimate fixed effects with random effects at different levels of aggregation. We used two different levels of aggregation, namely neighborhoods nested in municipalities, and police quadrants nested in police sectors, as a sensitivity analysis of the MAUP so that we may assess whether results of the moderation effects are affected by changes in the unit of analysis. With regards to the choice of the modelling approach, we use it precisely because the data are longitudinal and spatially nested. Our data set has three levels: Level 1 represents the longitudinal measures of homicide rates which were calculated for the two time periods used for our analyses, namely, the 15 months total prior to the implementation of the containment measures, and the 15 months after the containment measures were implemented. As said above, our independent variable is time which represents the time period before virus containment measures were implemented ($T = 0$) and the time period after ($T = 1$) (see Table 1). Our MST correlates are time-invariant. Level 2 represents the spatial units of analysis, that is, neighborhoods and police quadrants. Yet, since neighborhoods and police quadrants are nested in municipalities and police sectors correspondingly, we include these clusters as Level 3 data as we expected them to represent a significant source of variation –which they did according to the results of our regression analyses.

We first specified an unconditional growth model with time as the only fixed effect and random effects of time within neighborhoods and municipalities. This specification measures how much within-neighborhood variability in the homicide rates distribution is associated with change over time and how much variability is there across neighborhoods and municipalities (as random intercepts and slopes) over time as well. The unconditional growth model formulation is the following (Roback & Legler, 2021, pp. 335–336):

- Level 1 (timepoint within neighborhood):

$$Y_{ijk} = a_{ij} + b_{ij} time_{ijk} + \varepsilon_{ijk}$$

- Level 2 (neighborhood within municipality):

$$a_{ij} = a_i + u_{ij}$$

$$b_{ij} = b_i + v_{ij}$$

- Level 3 (municipality):

$$a_i = \alpha_0 + \tilde{u}_i$$

$$b_i = b_i + \tilde{v}_i$$

where $\epsilon_{ij} \sim N(0, \sigma^2)$,

$$\begin{bmatrix} u_{ij} \\ v_{ij} \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_u^2 & \\ \sigma_{uv} & \sigma_v^2 \end{bmatrix} \right), \text{ and}$$

$$\begin{bmatrix} \tilde{u}_i \\ \tilde{v}_i \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \tilde{\sigma}_u^2 & \\ \tilde{\sigma}_{u\,v} & \tilde{\sigma}_v^2 \end{bmatrix} \right).$$

In this formulation, at Level 1 the time trajectory for neighborhood j from municipality i is assumed linear, with intercept a_{ij} (i.e., homicide rate on T = 0) and slope b_{ij} (i.e., growth rate between T = 0 and T = 1); the error term ε_{ijk} captures the deviation between the growth trajectory of neighborhood j from municipality i and its observed homicide rates. At Level 2, a_i represents the actual mean intercept and b_i signifies the actual mean slope for all neighborhoods from municipality i, and u_{ij} and v_{ij} capture the deviation between while uij and vij capture the deviation between neighborhoods j's growth trajectory and the mean intercept and slope for municipality i. Lastly, α_0 is the actual mean intercept and β_0 is the actual mean growth rate over the entire set of neighborhoods, while $\tilde{u}_i$ and $\tilde{v}_i$ measure the difference between municipality i's overall growth and the mean intercept and slope for all neighborhoods (Roback & Legler, 2021).

The second specification is the conditional growth model in which the community strain measures are included into the equation as fixed effects in Level 1, while measuring the same variance components as in the previous specification. The third and final specification is the conditional growth with moderating effects model in which the interaction terms between time and MST measures are included into the equation as fixed effects. This specification allows to measure the moderation effects of time in the relationship between community strain and homicide

Table 4
Neighborhoods: Linear multilevel mixed-effects regression

	(1)	(2)	(3)
	Unconditional growth model	Conditional growth model	Conditional growth with moderated effects model
Fixed effects:			
Time*Econ. deprivation			−0.002
			(0.025)
Time*Density			0.006
			(0.025)
Time*Crowding			−0.014
			(0.027)
Time*Pop. mobility			0.040
			(0.028)
Time*Indian population			−0.044
			(0.030)
Time*Org. crime act.			0.028
			(0.026)
Time	−0.116***	−0.116***	−0.116***
	(0.025)	(0.025)	(0.025)
Econ. deprivation		0.113***	0.114***
		(0.016)	(0.020)
Density		−0.093***	−0.096***
		(0.016)	(0.020)
Crowding		−0.007	−0.0005
		(0.018)	(0.023)
Pop. mobility		−0.007	−0.027
		(0.018)	(0.022)
Indian population		−0.046**	−0.025
		(0.019)	(0.024)
Org. crime activity		0.193***	0.179***
		(0.015)	(0.020)
Intercept	0.664***	0.654***	0.654***
	(0.059)	(0.047)	(0.047)
Random effects:			
Municipality:			
SD Intercepts	0.143**	0.123**	0.123**
SD Time slopes	0.142**	0.123**	0.123**
Correlation	0.162	−0.106	−0.107
Neighborhood:			
SD Intercepts	0.969***	0.888***	0.889***
SD Time slopes	1.015***	0.969***	0.969***
Correlation	−0.899	−0.924	−0.924
SD (Residuals)	0.743***	0.745***	0.745***
N (Neighborhoods)	1824	1824	1824
N (Municipalities)	16	16	16
N (Time)	2	2	2
Obs.	3648	3648	3648
Fixed effects Pseudo-R2	0.004	0.088	0.089
Model Pseudo-R2	0.313	0.296	0.297
AIC	9243.4	9040.6	9077.2

*** $p < 0.01$, ** $p < 0.05$.

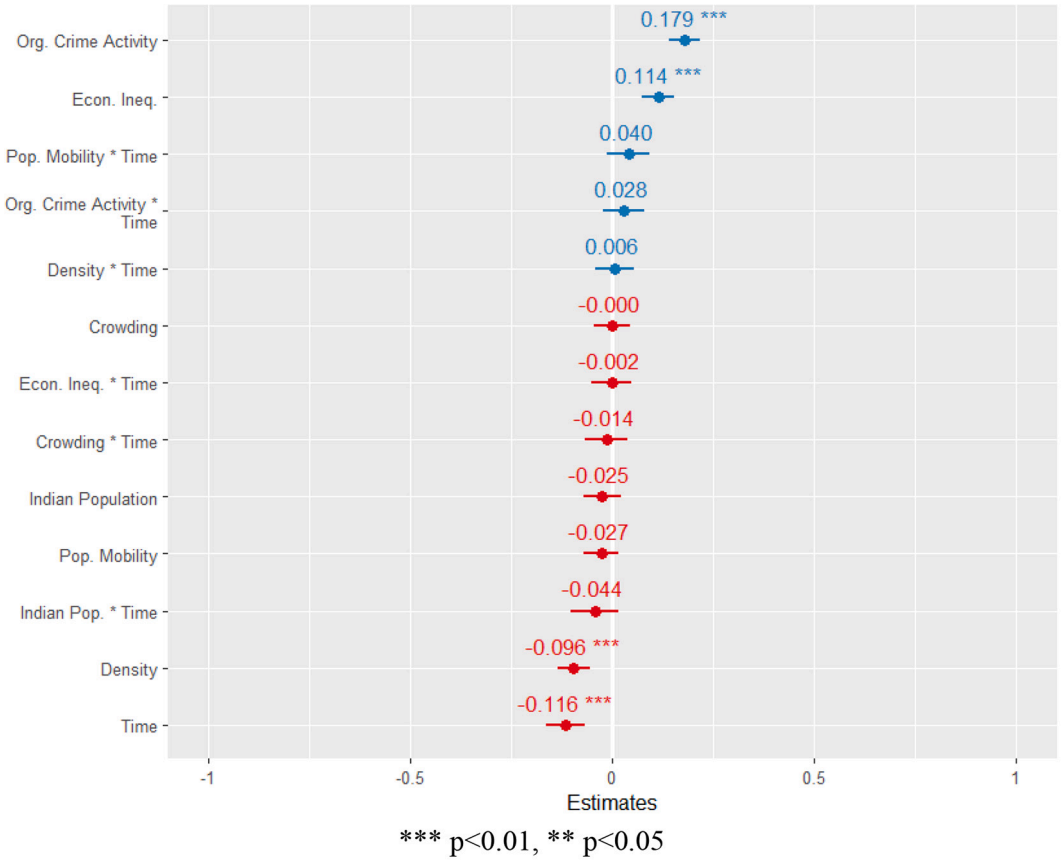


Fig. 5. Neighborhoods: Linear multilevel mixed-effects regression.
*** $p < 0.01$, ** $p < 0.05$.

rates. Finally, as said above, to assess the effects of the MAUP we repeated the same specifications with the use of police quadrants as units of analysis and compared results between the different spatial units.

The dependent variable was transformed to natural logarithms (1 + y if y = 0) and community strain measures were standardized using *Z*-scores. Log transformation was used to help reduce error skewness and heteroscedasticity, while Z-scores were used to help reduce multicollinearity in our moderation tests, eliminate the effect of different measurement units, and ensure comparability between regression coefficients. The method of restricted maximum likelihood (REML) was selected for estimating model parameters given that it separates the data used for estimating fixed effects from random effects and thus is better able to provide unbiased estimates of variance components (Roback & Legler, 2021). The software utilized were R (v. 3.3.1) and RStudio (v. 1.2.1335) in conjunction with the Linear and Nonlinear Mixed Effects Model (NLME) package (v. 3.1.148). Results with alpha <0.05 were considered statistically significant.

5. Results

Table 4 shows the results of our regression models for Mexico City neighborhoods. Model 1 is the unconditional growth model, Model 2 is the conditional growth model with no interaction effects, and Model 3 is the conditional growth model with interaction effects, that is, the tests of the moderation effect of the arrival of the pandemic and associated containment measures on the relationship between community measures of strain and homicide rates.

Results of Model 1 indicate that neighborhood homicide rates significantly decreased by 11.6% on average after virus containment measures were implemented. However, although statistically significant, this fixed average effect does not fully capture the variation of homicide rates across neighborhoods and municipalities over time given that the random intercepts and slopes at both levels of aggregation suggest that homicide rates neither decreased for all neighborhoods nor by the same amount –that is, the effect of social distancing measures on homicide was not homogeneous across neighborhoods or municipalities.

Results of Model 2 shows that population density and Indian speaking population were.

linearly and negatively correlated with homicide rates, that is, in the opposite direction as established by Strain theory. On the other hand, in agreement with the theory, economic deprivation and organized crime activity were positively correlated with homicide rates. Crowding and population mobility are not significantly associated with homicide. The strength of the association of organized crime activity with homicide as measured by drug dealing crimes is noteworthy. One standard deviation increase in organized crime activity would translate into a 19.3% average increase in the homicide rate. Thus, reducing homicide without reducing organized crime activity seems difficult for the case of Mexico City (Vilalta et al., 2021a, 2021b). Once again, Model 2 shows evidence of significant variability in the intercepts and slopes across neighborhoods and municipalities over time, suggesting that the statistical association between virus containment measures and homicide was not homogeneous across neighborhoods even after controlling for community strain.

Model 3 is the moderation effects model. In this regard, results confirm what we conjectured from the interaction plots before (see Figs. 3 and 4), namely, that the arrival of the pandemic did not impact the relationship between community strain and homicide rates at the neighborhood level. In this case, no interaction term is statistically significant, thus refuting the argument in previous studies that the pandemic and virus containment measures impacted homicide rates in

Table 5
Police quadrants: Linear multilevel mixed-effects regression

	(4)	(5)	(6)
	Unconditional growth model	Conditional growth model	Cond. growth and moderated effects model
Fixed effects:			
Time*Econ. deprivation			−0.020
			(0.025)
Time*Density			−0.009
			(0.035)
Time*Crowding			0.049
			(0.042)
Time*Pop. mobility			0.008
			(0.038)
Time*Indian population			−0.043
			(0.034)
Time*Org. crime act.			0.052
			(0.038)
Time	−0.150***	−0.150***	−0.150***
	(0.031)	(0.031)	(0.031)
Econ. deprivation		0.009	0.019
		(0.039)	(0.025)
Density		−0.053	−0.049
		(0.030)	(0.035)
Crowding		−0.290***	−0.314***
		(0.036)	(0.042)
Pop. mobility		−0.129***	−0.133***
		(0.033)	(0.037)
Indian population		0.257***	0.278***
		(0.028)	(0.037)
Org. crime activity		0.161***	0.136***
		(0.025)	(0.033)
Intercept	0.940***	0.932***	0.932***
	(0.051)	(0.048)	(0.048)
Random effects:			
Sector:			
SD Intercepts	0.304***	0.298***	0.298***
SD Time slopes	0.304***	0.299***	0.298***
Correlation	−0.342	−0.402	−0.406
Quadrant:			
SD Intercepts	0.901***	0.885***	0.886***
SD Time slopes	0.902***	0.891***	0.893***
Correlation	−0.793	−0.852	−0.852
SD (Residual)	0.641***	0.644***	0.645***
N (Quadrants)	847	847	847
N (Sectors)	72	72	72
N (Time)	2	2	2
Obs.	1694	1694	1694
Fixed effects Pseudo-R2	0.006	0.150	0.151
Model Pseudo-R2	0.530	0.526	0.525
AIC	4237.5	4117.4	4155.6

*** $p < 0.01$, ** $p < 0.05$.

relation to strain. Instead, we provide an absence of evidence of such argument –at least there is no evidence of a linear effect at the neighborhood level of analysis. To put it differently, homicide rates changed, but these changes were not affected by the interaction between the pandemic and the virus containment measures with community strain. In this sense, most results of Model 3 coincide with those of Model 2. Population density remained negatively correlated with homicide, while economic deprivation and organized crime activity remained positively correlated with homicide rates. Indian speaking population lost statistical significance after the introduction of the interaction terms. Fig. 5 shows graphically the results of Model 3 for easier interpretation.

Table 5 show the results of our mixed effects regression models for police quadrants. Interaction term coefficients in Model 6 are not significantly associated with homicide rates, suggesting again a lack of evidence of containment measures moderating the relationship between community strain and homicide, now at the police quadrant level. However, interestingly these results provide evidence of the MAUP as they differ from results in the neighborhood models. For instance, we find that while neither economic deprivation nor population density are significantly associated with homicide at the police quadrant level of analysis. On the other hand, household crowding and population mobility are negatively associated with homicide, and Indian speaking population is now positively associated for the case of police quadrants as compared to neighborhoods. What this means is that relationships are sensitive to the unit of analysis being used. Fig. 6 shows graphically the results of Model 6 for police quadrants for easier interpretation. Tables A2 and A3 in the appendix present the descriptive statistics of the estimation samples and the results of collinearity tests respectively. Multicollinearity tests indicate that models are within acceptable limits. We discuss these results in the next section.

6. Discussion and conclusion

Different theoretical arguments have been presented to explain changes in crimes rates due to Covid-19 virus containment measures. Strain theory is among the theories that have been evoked to explain these changes. However, we are not aware of a study testing whether the pandemic and containment measures interacted with strain to alter crime trends. For this reason, in this study we test whether the implementation of virus containment measures in Mexico City modified the relationship between structural strain and homicide, as one previous study conducted before the pandemic has already linked macro-level

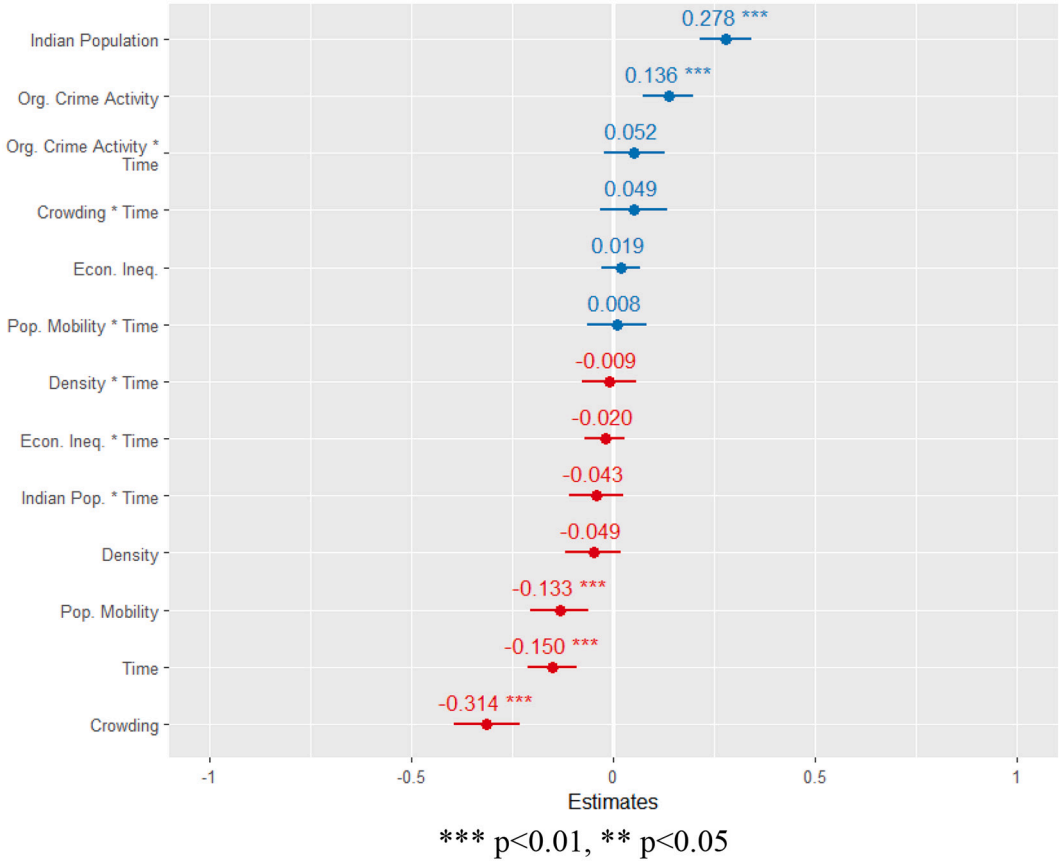


Fig. 6. Police quadrants: Linear multilevel mixed-effects regression.
*** p < 0.01, ** p < 0.05.

strain theory with homicide in Mexico City (Vilalta et al., 2021a). We found evidence of community strain indicators predicting homicide rates, but no evidence of containment measures modifying the long-term relationship between community strain and homicide rates. Our evidence is that correlations between community strain indicators and homicide rates remained unaltered between the pre-containment measures period and containment measures period. As such, we do not find evidence from which to link structural strain with the homicide drop observed after containment measures were implemented.

In addition, previous correlations seem sensitive to the modifiable areal unit problem (MAUP), as evidenced by the difference in results when using neighborhoods versus police quadrants as units of analysis. This is an issue that many studies using geographically aggregated data leave aside. However, this study shows evidence of this problem, which cannot be eliminated by turning our eyes other side and looking at one unit of analysis at a time. We included a sensitivity analysis of our results not with the expectation of disproving MST, which we did not, but with the hope that it would highlight the existence of the MAUP and encourage other researchers to conduct sensitivity analysis of their statistical results.

It is important to note the limitations of this study. First, the limited generalizability of the findings outside the Mexico City context and the limited generalizability of the findings considering that homicide is the only crime considered in this study.[10] As we said in the introduction, we focused on homicide crimes given they barely increased following the implementation of the containment measures, in contrast with other crimes in Mexico City and homicides other Latin American cities such as Lima, Peru, Cali, Colombia, and Rio de Janeiro in Brazil (Nivette et al., 2021; Vilalta et al., 2022). In this respect, it is important to note that many homicides in Mexico City are associated with the organized crime activity and economy, which perhaps is less elastic to the pandemic and to structural strains than other crimes. However, this is a hypothesis we did not pursue in this study. Another limitation are measurement issues such as the use of proxy measures to depict strained communities or the use of an ad hoc Mexico City component index as proxy measure of economic deprivation and inequality. Data availability limitations make it impossible to have exact measures of the characteristics of strained communities as considered in MST. However, our choice of variables covers all of the compositional characteristics that MST theorizes correlate positively with community crime, namely, economic deprivation and inequality, density, crowding, population mobility, and ethnicity. As such, we believe these proxy measures will not impact our findings substantively.

Two interrelated statistical limitations are the potential bias resulting from omitted variables and our time-invariant treatment of MST correlates. Our use of random place-intercepts and time-slopes at different levels of analysis (i.e., neighborhoods nested in municipalities, and police quadrants nested in police sectors) is one way we use to deal with the omitted variable bias. Our analytical strategy is to partition the unobserved heterogeneity into different yet relevant levels of analysis so that in better capturing it, it does not impact our fixed effects estimates. However, the time-invariant treatment of MST correlates is unavoidable as they are census-based measures. The only statistical strategy possible in this respect is to include the time dimension both as a fixed and random effect, as well as TO estimate the moderation effect of time on the relationship between each MST correlate and the time period itself, which is what we do in this study. Of course, anything we may do with observational data, including incorporating the time dimension into the equation, can fully capture all the possible effects that the pandemic may

[10] We thank one of the reviewers for pointing out these two limitations.

have had on the MST correlates. The end result being to limit the scope of any theory test including this one. One final limitation is that we did not attend was whether containment measures altered opportunity patterns for homicide. Even though opportunities are distinct from strain-related impulses (South & Cohen, 1985), we did not control for structural opportunities for homicide which may have also been affected by containment measures.

In sum, we found that the link based on strain theory premises regarding the homicide drop and the Covid-19 pandemic has no universal footing. Likewise, the effects of containment measures were not spatially uniform, making "on average" statements neither exact nor sufficiently precise. Finally, while MST seems able to predict homicide rates, predictions are sensitive to the MAUP. The dominance of organized crime activity in Mexico City partially limits the generalizability of our findings. In this sense, future case studies and spatial analyses of cities can provide additional ideas regarding MST ad hoc specifications and further delineate some of the local relationships that we may be missing to detect with the use of global models.

Appendix A

Table A1
Principal component analysis for the Economic deprivation index

	Neighborhood	Police Quadrants
	Loadings	
Male pop. Between 18 and 24 years old (%)	0.556	0.564
Pop. not beneficiary of public medical services (%)	0.588	0.584
Pop. 15 or more w/ incomplete elementary schooling (%)	0.588	0.583
Eigenvalue	1.854	2.281
Variance (%)	61.8	76.0

Table A2
Estimation sample descriptive statistics

Variable	Mean	Std. Dev.	Min	Max
Neighborhoods:				
Homicide rate (LN)	0.608	0.889	0.000	9.904
Time	0.500	0.500	0.000	1.000
Econ. deprivation	0.000	1.356	−4.889	6.790
Density	0.000	0.998	−1.195	17.792
Crowding	0.000	0.996	−2.263	11.891
Pop. mobility	0.000	0.996	−1.234	11.254
Indian population	0.000	0.996	−0.864	8.168
Org. crime activity	0.000	1.000	−0.447	15.104
Police quadrants:				
Homicide rate (LN)	0.854	0.936	0.000	8.805
Time	0.500	0.500	0.000	1.000
Econ. deprivation	0.000	1.510	−5.265	6.329
Density	0.000	1.000	−1.818	4.289
Crowding	0.000	1.000	−5.430	2.511
Pop. mobility	0.000	1.000	−1.595	6.710
Indian population	0.000	1.000	−0.913	16.011
Org. crime activity	0.000	1.000	−0.653	9.860

Table A3
Collinearity tests for conditional growth and moderated effects models 3 and 6 respectively

	VIF	Increased Std. Error	Tolerance
Model 3 for Neighborhoods:			
Time	1.00	1.00	1.00
Econ. deprivation	2.61	1.62	0.38
Density	1.66	1.29	0.60
Crowding	1.82	1.35	0.55
Pop. mobility	1.81	1.34	0.55
Indian population	2.28	1.51	0.44
Org. crime activity	1.73	1.31	0.58
Time*Econ. deprivation	2.84	1.68	0.35
Time*Density	1.67	1.29	0.60
Time*Crowding	1.90	1.38	0.53
Time*Pop. mobility	1.93	1.39	0.52
time*Indian population	2.33	1.53	0.43
Time*Org. crime activity	1.73	1.31	0.58
Model 6 for Police Quadrants:			
Time	1.00	1.00	1.00
Econ. deprivation	4.75	2.18	0.21

(*continued on next page*)

Table A3 (*continued*)

	VIF	Increased Std. Error	Tolerance
Density	1.61	1.27	0.62
Crowding	3.31	1.82	0.30
Pop. mobility	1.53	1.24	0.65
Indian population	2.32	1.52	0.43
Org. crime activity	1.80	1.34	0.55
Time*Econ. deprivation	5.81	2.41	0.17
Time*Density	1.73	1.31	0.58
Time*Crowding	3.92	1.98	0.25
Time*Pop. mobility	1.83	1.35	0.55
time*Indian population	2.52	1.59	0.40
Time*Org. crime activity	1.91	1.38	0.52

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