Shaking Criminal Organizations: Earthquakes and Organized Crime

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Abstract

There is mixed evidence regarding how organized crime organizations become altruistic or violent after a natural disaster. This paper analyses the effect of the 2017 earthquakes that hit Mexico on the incidence of violence and altruism committed by large and local criminal organizations. Using a difference-in-differences methodology; there is a significant increase in the probability that a municipality suffers an incidence of violence committed by local criminal organizations by 5%, but no effect on violence incidences committed by large criminal organizations. A Spatial Point Pattern Test (SPPT) reveals that this increase in violent crimes is localized in six municipalities, mostly forming a spatial cluster in Mexico City. In addition, the results show that large criminal organizations behave non-altruistically, whereas local criminal organizations increase their social altruism activities by 7%. In all, the earthquakes seem to affect the behavior of local criminal organizations but not that of large criminal organizations.

Keywords: Organized crime, Natural disasters, Earthquakes, Social altruism.

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1 Introduction

Do natural disasters increase the social altruism of criminal organizations or make criminal organizations more violent? Frailing and Harper (2017) propose to use theories such as the social disorganization theory (Shaw and McKay, 1942) and the therapeutic community theory (Fritz, 1996) in order to get some guidance to answer this question. However, the predictions of these theories are mixed. The therapeutic community theory predicts that natural disasters decrease violence committed by organized crime due to increased social altruism. Nevertheless, the social disorganization theory predicts increased violence committed by criminal organizations due to increased social disorganization after a natural disaster.

In this paper, we examine the effects of the 2017 earthquakes that hit Mexico on the incidence of violence and altruism committed by criminal organizations. We use two sources of data obtained from the internet through machine learning algorithms: the Organized Criminal Violence Event Data (Osorio and Beltrán, 2019) and the Mapping Criminal Organizations Data (Sobrino, 2021). These data contain information regarding incidences of violence (homicides, kidnapping, extortion, torture, among others) and altruism (services, public goods, or gifts) committed by large and local criminal organizations at the municipality level.

Using a difference-in-differences methodology, the results show a significant increase in violence committed by local criminal organizations (5%) but no effect on violence incidences committed by large criminal organizations. Then, we implement a Spatial Point Pattern Test (SPPT) to identify the municipalities impacted by the increase in incidents of violence by local criminal organizations. We find that this increase is centralized around four municipalities in Mexico City (Coyoacan, Cuauhtemoc, Iztacalco, and Venustiano Carranza), while the remaining two are in the states of Puebla (Zapotitlán) and Tlaxcala (Tlaxcala city). Finally, the results show a significant increase in the incidences of altruism by local criminal organizations (7%) but no effect on large criminal organizations.

This paper contributes to the natural disasters and crime literature by examining earthquakes' casual and spatial effects on organized crime in several ways. First, this paper contributes to the qualitative research on the impact of natural disasters on violence by criminal organizations. Qualitative evidence points to an increase in gang activities after a disaster (Cromwell et al., 1995). We confirm increased violence committed by organized crime after a disaster, with local criminal enterprises mainly driving it. Second, there is also qualitative evidence that organized crime supports communities impacted by disasters (Rankin, 2012). This paper confirms the findings from this literature. In particular, we observe that local criminal organizations behave altruistically. Third, using spatial methods, this paper allows policymakers to identify the regions with the greatest increase in the levels of violence by local criminal organizations.

To sum up, this paper contributes to our understanding of the geographies of Organized Crime after a natural disaster combining novel data sources, causal, and spatial methods. The data obtained from the internet permits a quantitative study of Criminal Organizations' behavior regarding violence and altruism after a disaster. The causal methods permit the identification of whether there is a change in the behavior of criminal organizations. Finally, the use of spatial methods provides information to policymakers regarding the geographic areas where efforts should be concentrated to reduce incidents of violence.

2 Natural Disasters and Organized Crime

2.1 Theoretical Basis

Frailing and Harper (2017) propose to use criminology theories to understand the effect of natural disasters on organized crime behavior. Among these theories are the *social disorganization* theory (Shaw and McKay, 1942), the *routine activity* theory (Cohen and Felson, 1979), the *therapeutic community* theory (Fritz, 1996), and the *resilience* hypothesis (Frailing and Harper, 2017). We briefly describe these four theories to give context to our findings below.

The social disorganization theory explains the rise in violence committed by criminal organizations after a natural disaster through a change in factors such as poverty, family disruption, and unemployment in certain geographical areas (Shaw and McKay, 1942). Specifically, regions particularly affected by social disorganization factors —after a natural disaster— see an increase in the number of individuals experiencing negative emotions, which raises the likelihood of those individuals entering into a criminal organization. Similarly, the routine activity theory predicts increased criminal activity after disasters because fewer resources are dedicated to preventing crime, as authorities are absorbed by rescue and relief efforts (Cohen and Felson, 1979).

Conversely, the therapeutic community theory predicts that natural disasters decrease organized crime. In particular, this theory suggests that natural disasters generate empathy and social cohesion (Fritz, 1996). This is a consequence of social feelings experienced by communities —affected by natural disasters—, due to human and material losses. Social altruism permeates criminal organization members, who cease committing certain crimes to support the communities hit by natural disasters.

Finally, the resilience hypothesis proposes compensating effects of natural disasters on violence committed by criminal organizations (Frailing and Harper, 2017). In particular, natural disasters decrease the number of sellers and buyers of certain illegal markets due to migration or lack of income during the short run. However, in the medium run, natural disasters increase substance abuse or intensify the use of illegal drugs to cope with stress. Thus, there is an influx of new dealers to try to capture the market. The illegal drug market is re-established on both the supply and demand side. During this process, it is possible to see some increases in the levels of violence, but these levels decrease as illegal markets are re-established.

2.2 Empirical Evidence

In line with the social disorganization theory, existing empirical research for New Orleans after Hurricane Katrina finds that violent crime was significantly higher in neighborhoods with concentrated disadvantages (Weil et al., 2021). The literature also documents changes in organized crime structures following natural disasters. After the 2010 earthquake in Haiti, there was an increase in criminal organizations that developed from established gangs of young people from fragile neighborhoods (Global Initiative, 2022). Evidence points to an increase in young people participating in criminal organizations after Hurricane Andrew, which hit Florida in 1992 (Cromwell et al., 1995).

There is also evidence that goes accordingly with the therapeutic community theory. After the August 2021 earthquake in Haiti, criminal organizations helped with the coordination of certain international humanitarian aid as well as with the distribution of food, water, and medicine (Niño and González, 2022). The control of a few criminal figures over the 95 gangs operating in the capital possibly facilitated the distribution of resources during the emergency (Walker, 2022). Similarly, after the earthquake that hit the Tohoku region in Japan in 2011, the Yakuza provided food and emergency supplies to the damage region (Rankin, 2012).

Suggestive evidence in favor of the resilience hypothesis includes research on Hurricane Katrina. Namely, results indicate a disruption in the drug market with the negative consequence of increasing lethal violence in the short run; however, in the medium run, the influx of new dealers and users bounced back to the illegal drug market, with a subsequent decrease in lethal violence (Frailing and Harper, 2017).

In sum, we observe the following: (a) there is no unified theory regarding the violence or altruism of organized crime in natural disasters. (b) There is little empirical evidence regarding the effects of disasters on violence committed by organized crime; few of these studies show causal effects. Furthermore, (c) there is qualitative evidence that organized crime supports disaster-affected communities (Japan 2011, Haiti 2021), but few studies do so with quantitative evidence.

3 Background

3.1 The September 2017 Earthquakes in Mexico

Two powerful earthquakes struck Mexico in September 2017, causing an estimated damage of 0.5% of the country's GDP (CENAPRED, 2017). These earthquakes impacted 689 of over 2,457 municipalities (see Figure I). The epicenter of the first earthquake with a magnitude of 8.2 on the Richter scale, which occurred on September 7, was in Pijijiapan, Chiapas (southeast Mexico). The epicenter of the second earthquake with a magnitude of 7.1 on the Richter scale, which occurred on September 19, was in Axichiapan, Morelos (central Mexico). The earthquakes impacted Oaxaca, Chiapas, Veracruz, Mexico City, Morelos, Puebla, Estado de Mexico, Tlaxcala, and Guerrero municipalities. It is estimated that the earthquakes impacted 775,000 individuals, 72,000 households, 13,900 schools, 264 hospitals, and around 500 fatalities (CENAPRED, 2017).

3.2 Homicides and organized crime in Mexico

During 2000-2006, Mexico maintained relatively low homicide rates (around ten homicides per 100,000 inhabitants). However, for 2007-2012, the homicide rate increased drastically to 22 homicides per 100,000 inhabitants (Brown and Velasquez, 2017). For the 2013-2015 period, the rate decreased to 17. However, in 2017, the number of homicides was 31,174, the highest number from 2000-2017.

Why did the number of homicides in Mexico increase dramatically? The explanations for the increase in homicide rates can be grouped into three possible causes: (1) a stricter internal policy in the fight against drugs, (2) external factors, and (3) socioeconomic aspects.

Lindo and Padilla-Romo (2018) analyzes the strategy of President Calderon (2006-2012) to capture leaders of a drug trafficking organization. They find that the capture of a leader increases the homicide rate. However, the authors point out that these captures only explain 31.5% of the increase in the homicide rate during the period 2006-2010. Castillo et al. (2014) find evidence that a reduction in the supply of cocaine from Colombia (Mexico's main supplier) could explain between 10% and 14% of the increase in violence in Mexico. Finally, Enamorado et al. (2016) finds that an increase of one point in the Gini coefficient (greater inequality) represents an increase of around six homicides per 100,000 inhabitants from 2007-2010.

4 Data and Empirical Strategy

4.1 Data

We use three sources of data to analyze the effects of earthquakes on incidences of violence and altruism: the National Center for Disaster Prevention (CENAPRED, 2017), the Organized Criminal Violence Event Data (Osorio and Beltrán, 2019), and the Mapping Criminal Organizations Data (Sobrino, 2021). The National Center for Disaster Prevention (CENAPRED, 2017) provides information regarding the municipalities impacted by the earthquakes. There are 2,457 municipalities in Mexico, and the earthquakes impacted 689 municipalities. The municipalities impacted by the earthquakes will be our treatment group, and the rest will be our control group.

The Organized Criminal Violence Event (OCVED) records daily data at the municipal level, detailing violent incidents such as homicides, kidnapping, extortion, torture, and others committed by members of criminal organizations. The data includes information about nine large criminal cartels (Beltran Leyva, Cartel de Jalisco Nueva Generación, Cartel de Juarez, Cartel de Sinaloa, Cartel de Tijuana, Cartel del Golfo, La Barbie, La Familia Michoacana, and Los Zetas), 71 local criminal organizations, and incidents of violence by unidentified criminal groups.

OCVED data utilizes 105 sources of information, including national and local newspapers and government agencies, and machine learning algorithms to classify news related to violence committed by criminal organizations from January 2000 to December 2018. These categories are distinct and do not overlap, as each news article is assigned to a specific organization using a set of fixed dictionaries. Thus, the algorithm classifies each news article based on the organization, action, location, and time. Based on the OCVED data, we generate two dichotomous variables (large criminal organizations and local criminal organizations) that measure the incidence of violence per month per municipality from January 2017 to September 2018 (eight months before and twelve months after the earthquakes). Our sample consists of 51,597 observations (2,457 municipalities x 21 months).

The Mapping Criminal Organizations (MCO) provides information regarding whether the criminal organizations provide services, public goods, or gifts to the population (a proxy for altruism). A panel of 79 criminal organizations was constructed from 1990 through July 2021. We separate these organizations into two groups: nine large criminal organizations (Beltran Leyva, Cartel de Jalisco Nueva Generación, Cartel de Juarez, Cartel de Sinaloa, Cartel de Tijuana, Cartel del Golfo, La Barbie, La Familia Michoacana, and Los Zetas), and the rest of criminal organizations as local criminal organizations. Using the MCO data, we generate two dichotomous variables (large criminal organization and local criminal organizations) that measure whether a municipality per year reported at least one act of altruism by a criminal organization from 2015 to 2018. Our sample consists of 9,808 observations (2,452 municipalities x 4 years).

Table 1 presents summary statistics. Panel A presents the results using the Organized Criminal Violence Event (OCVED) data regarding the incidence of violence by criminal organization groups. This panel suggests that around 5% of the municipalities in Mexico suffer an incidence of violence by large and local criminal organizations. In particular, large criminal organizations commit 2.5%, and local criminal organizations commit 2.4%. Panel B shows descriptive statistics using the Mapping Criminal Organizations (MCO) data regarding altruism committed by large and local criminal organizations at the municipality level annually. We observe that around 5% of the municipalities report at least one incidence of altruism by criminal organizations. In particular, large criminal organizations commit 3.5% , and local criminal organizations commit 1.4%.

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4.2 Empirical Strategy

4.2.1 Difference-in-Differences

First, we estimate a difference-in-differences model. The difference-in-differences provides the average effect of the earthquakes on the variables of interest. The specification is given as follows:

$$Y_{mty} = \alpha + \beta \text{ Earthquake}_{mty} + a_m + \gamma_t + \nu_y + e_{mty} \quad (1)$$

where Y_{mty} is the outcome of interest for municipality m in month t and year y. Earthquake_{mty} is a dummy variable that equals one from September 2017 through September 2018 for the municipalities impacted by the earthquakes and zero otherwise. a_m are municipality-fixed effects, γ_t are month fixed-effects, and ν_y are year fixed effects. In order to take into account the population heterogeneity at the municipal level, the specification is weighted by the population at that level. We cluster the standard errors at the municipality level. In the case of the Mapping Criminal Organizations variables, given that the data is collected annually, the variable Earthquake is a dummy variable that equals one from 2017 to 2019 for the municipalities impacted by the earthquakes, meaning that we do not include month fixed effects.

We employ a log-transformation of the dependent variable as it allows us to interpret the results as approximations of percentage changes. In addition, a log-transformation of the dependent variable permits addressing the issue of over-dispersion in the distribution. In many municipalities, our dependent variables tend to report zero incidents, while certain municipalities experience large incidences at specific times, resulting in a right-tailed distribution. A log-transformation helps to alleviate this overdispersion. Nevertheless, in the robustness section, we run our results using the original dichotomous variable (a linear-linear model) to show that the results are not driven by the functional form selected.

4.2.2 Spatial Point Pattern Test (SPPT)

In order to get information regarding the geographical changes based on the causal impacts identified by the differences-in-differences results, we use a Spatial Point Pattern Test (SPPT) on the Organized Criminal Violence Event (OCVED) database reports. The SPPT (Andresen, 2009) focuses on the geographic coordinates where organized crime groups commit violent acts. We aimed to identify notable changes in violent incidents across municipalities before and after the 2017 earthquakes.

We divided the OCVED database into two separate datasets for our methodology. The first dataset, called the 'Base Dataset,' includes violent events recorded in each municipality for the eight months previous to the earthquakes. The violent incidents in the data correspond to homicide, kidnapping, extortion, and other crimes attributed to organized crime. The second dataset, the 'Test Dataset,' contains violent incidents reported in the following 12 months. The main objective of the SPPT is to determine differences between the violence patterns in both datasets. To achieve this, we calculated the proportion of violent incidents in each defined area from the base dataset. Then, we randomly selected 85% of the points from the test dataset with replacement and calculated the proportion of post-earthquake violent incidents for each sample. Following the recommendations of Wheeler et al. (2018), we repeated this sampling and calculation process 200 times to ensure accuracy. We also analyzed the significant difference in proportions using resampling that incorporates all the data from both datasets.

Next, we created a 95% nonparametric confidence interval by ranking all the random samples in ascending order and removing the top and bottom 2.5%. We then compared the percentage of violent incidents in the base dataset's defined area to this confidence interval. If the percentage from the base dataset is within the confidence interval, it indicates a similar distribution of violent incidents in both datasets. If the percentage is outside this confidence interval, then there is significant evidence that both proportions are different, meaning violent crime has either gone up or down. Overall, this algorithm allowed us to determine if there was a statistically significant change in the violent patterns exhibited by local criminal organizations following the earthquakes. It is important to highlight that the SPPT methodology is limited to using OCVED records because geographical coordinates (x,y) are necessary for its application. Unfortunately, the MCO data does not provide the geographical reports' coordinates (x,y).

5 Results

5.1 Difference-in-Differences Results

Table 2 shows the difference-in-differences results. Columns (1) and (2) explore incidences of violence by type of criminal organizations after the earthquakes. We find no increase in incidences of violence for large criminal organizations. Conversely, local criminal organizations increased the level of violence by 5.3%. Then, Columns (3) and (4) explore incidences of altruism by type of criminal organizations after the earthquakes. Large criminal organizations behave non-altruistic, whereas local criminal organizations increased their social altruism activities by 7.0%

Then, we conduct the following robustness checks regarding the difference-in-differences results: (1) using a placebo test to check the parallel trends assumption, (2) using a linear-linear form to test the sensibility of the results to a different functional form, and (3) using a bounding methodology to check the sensibility of the results to omitted variable bias.

First, we follow Brassiolo (2016) to test the parallel trends assumption (the treatment and control group follow the same trend before the earthquakes) using a placebo test. The idea is to reference a period when the event did not occur (placebo) and show no effects using the same difference-in-differences specification. If it is found that there are effects, then it means that other variables are affecting our results, and we do not have support for the parallel trends assumption. Thus, we assume that the event occurred in September 2016 instead of September 2017. Table 3 Panel A presents the results using this placebo test. As expected, we find no effects of the placebo earthquakes on local criminal organizations' violence (Column 2) and local criminal organization's altruism (Column 3).

Second, we use a log-linear form to interpret the results in percentage change. Nevertheless, the results may be driven by using this particular functional form. We use a linear-linear form to check the sensibility of our results to the functional form. That is, we use the probability that a municipality suffers an action of violence or altruism instead of the logarithm of such probability. Table 3 Panel B presents the results using a linear-linear form. The results confirm that earthquakes increased local criminal organization's violence (Column 2) and altruism (Column 4).

Third, we check the sensibility of our results to omitted variable bias. The placebo test supports the parallel trends assumption and that the earthquakes drive our results. To confirm that other omitted variables do not drive our results, we conduct a test based on a bounding methodology proposed by Oster (2017). This methodology generates a bound around the parameter of interest. This bound is generated based on assumptions regarding the R^2. To generate this bound, it is suggested to use 1.3 times the value of the R^2 in the main specification (Oster, 2017). If the bound excludes the zero, then it implies that the results are robust to the problem of omitted variable bias. Table 3 Panel C presents the results using the bounding methodology. The bounds are presented in brackets. In the case of incidences of violence by local criminal organizations, we find that the bound is [0.045, 0.080]. In the case of incidences of altruism by local criminal organizations, we find that the bound is [0.042, 0.119]. These results confirm that our results are robust to the problem of omitted variable bias.

One limitation of the OCVED data is that it provides information regarding an act of violence committed by criminal organizations. Yet, we do not have information on the violence they committed. Data from the National Public Safety System (NPSS) is used to obtain more information on the increased acts of violence. The National Public Safety System (NPSS) collects monthly data for crimes reported to the police at the municipality level. We analyse the following crimes related to organized crime: homicides, petty drug crime, extortion, and kidnapping. We use rates per month per municipality per 100,000 inhabitants from January 2017 to September 2018 (eight months before and 12 months after the earthquake). Our final sample comprises 51,597 observations (2,457 municipalities x 21 months). We use the same difference-in-differences specification (equation 1). Table 4 shows the difference-in-differences results. The results show no statistically significant effects on homicides and petty drug crime rates. However, the results show that extortion rates increased by 2.9% and kidnapping rates by 3.9%.

In the case of Mexico, earthquakes do not affect the behavior of large criminal organizations regarding violence and altruism. On the contrary, local criminal organizations change their behavior after the earthquakes. These types of criminal enterprises had to strengthen ties with local communities, but at the same time, they had to intensify their criminal activities, such as extortion and kidnapping.

5.2 Spatial Results

The causal methodology helps us understand which variables and groups have become more violent. The spatial methodology, however, allows us to pinpoint the specific geographical areas where these changes occurred. We utilized the Spatial Point Pattern Test (SPPT) using OCVED records to identify the municipalities where local criminal organizations have committed increased violence. The results of the SPPT for local criminal organizations indicate that six municipalities reported a significant rise in crime (Figure II).

Out of the six municipalities, four are located in Mexico City (Coyoacan, Cuauhtemoc, Iztacalco, and Venustiano Carranza), while the remaining two are in Puebla (Zapotitlán) and Tlaxcala (Tlaxcala city). Interestingly, most municipalities that have seen a significant increase in crime are situated in Mexico City (as shown in Figure II). Therefore, the spatial agglomerations in Mexico City are likely due to the criminological conditions in neighboring municipalities where local criminal groups operate.

6 Discussion and Conclusion

We analyse the effects of earthquakes on incidences of violence and altruism committed by large and local criminal organizations in Mexico. Using a difference-in-differences methodology, the results show a significant increase in violence committed by local criminal organizations but no effect on violence committed by large criminal organizations. In addition, there is a significant increase in the incidences of altruism by local criminal organizations but no effect on large criminal organizations.

Then, we examine the effects of earthquakes on incidents of violence related to criminal organizations, such as homicides and kidnapping rates. We observe no effects on homicide rates but an increase in kidnapping rates. Finally, we implement a Spatial Point Pattern Test (SPPT) to identify the municipalities impacted by the increase in incidents of violence by local criminal organizations. This increase is centralized around four municipalities in Mexico City, while the remaining two are in Puebla and Tlaxcala.

There is qualitative evidence that after a disaster, gang activity increases (Cromwell et al., 1995). We find similar results in the Mexican context, where local criminal organizations increase violence after a disaster. There is also qualitative evidence that organized crime supports communities impacted by disasters (Rankin, 2012). This paper finds that local criminal organizations behave in an altruistic form.

A question that remains open is why heterogeneous effects are observed in crimes related to organized crime: increases in kidnapping but no effects in homicides. One potential explanation is that large criminal organizations are more involved in homicide rates. Thus, if the earthquakes do not impact large criminal organizations, we should observe no effects on homicide rates. In the case of the local criminal organizations, they have more information regarding wealthy individuals in their localities. Moreover, after being affected by the disasters, these wealthy individuals can be the target of being kidnapped. Thus, the rise in kidnappings may indicate that this crime is a crime of opportunity that local gangs can exploit during the chaos resulting from an environmental catastrophe.

Another issue that deserves to be explored in greater detail is the increase in incidents of violence in the municipalities of Mexico City by criminal organizations after the disaster. The first explanation could be related to the social disorganization hypothesis. Maybe those municipalities were the most impacted by unemployment (Shaw and McKay, 1942), as well as shifts in the supply of young people to criminal enterprises due to school infrastructure damages (Cromwell et al., 1995), and high rates of cartel recruitment in recent years (Prieto-Curiel et al., 2023). Another hypothesis could suggest that Mexico City suffered a dynamic similar to the effects of Hurricane Katrina in New Orleans, where the disaster affected the illegal market structure, leading to an increase in criminal activity by organized crime groups (Frailing and Harper, 2017).

In terms of public policy, this study provides information on which crimes (kidnapping) and criminal organizations (local) increased their levels of violence. Likewise, using spatial statistical techniques allows public policymakers to identify the localities with the greatest increase in the levels of violence by local criminal organizations.

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7 Figures and Tables

Table 1: Descriptive Statistics

	Mean	S.D.	N
Panel A: Violence			
Large Criminal Organization Violence (Yes=1)	0.025	0.156	51,597
Local Criminal Organization Violence (Yes=1)	0.024	0.154	51,597
Panel B: Altruism			
Large Criminal Organization Altruism (Yes=1)	0.035	0.185	9,808
Local Criminal Organization Altruism (Yes=1)	0.014	0.120	9,808

SOURCE: Panel A uses the Organized Criminal Violence Event (OCVED), and Panel B uses the Mapping Criminal Organizations (MCO) data.

Table 2: Difference-in-differences Specification

	Large CO Violence	Local CO Violence	Large CO Altruism	Local CO Altruism
	(1)	(2)	(3)	(4)
Earthquake	0.022	0.053***	0.017	0.070**
	(0.015)	(0.017)	(0.011)	(0.028)
R^2	0.41	0.37	0.73	0.58
Observations	51597	51597	9808	9808
Baseline FE	X	X	X	X

SOURCE: Columns (1) and (2) use the Organized Criminal Violence Event (OCVED), and Columns (3) and (4) use the Mapping Criminal Organizations (MCO) data.
NOTES: Baseline fixed effects are included at the municipality, month, and year in Columns (1) and (2). Baseline fixed effects are included at the municipality and year in Columns (3) and (4). Robust standard errors are clustered at the municipal level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Robustness Checks

	Panel A: Placebo			
	Large CO Violence	Local CO Violence	Large CO Altruism	Local CO Altruism
	(1)	(2)	(3)	(4)
Earthquake	-0.002	-0.023	0.027	0.027
	(0.015)	(0.023)	(0.022)	(0.020)
R^2	0.40	0.32	0.76	0.67
Observations	51597	51597	7356	7356
Baseline FE	X	X	X	X

	Panel B: Linear Function			
	Large CO Violence	Local CO Violence	Large CO Altruism	Local CO Altruism
	(1)	(2)	(3)	(4)
Earthquake	0.032	0.077***	0.025	0.101**
	(0.022)	(0.025)	(0.016)	(0.041)
R^2	0.41	0.37	0.73	0.58
Observations	51597	51597	9808	9808
Baseline FE	X	X	X	X

	Panel C: Oster's Bounds			
	Large CO Violence	Local CO Violence	Large CO Altruism	Local CO Altruism
	(1)	(2)	(3)	(4)
Earthquake	0.022	0.053***	0.017	0.070**
	[0.003, 0.074]	[0.045, 0.080]	[-0.024, 0.096]	[0.042, 0.119]
R^2	0.41	0.37	0.73	0.58
Observations	51597	51597	9808	9808
Baseline FE	X	X	X	X

SOURCE: Columns (1) and (2) use the Organized Criminal Violence Event (OCVED), and Columns (3) and (4) use the Mapping Criminal Organizations (MCO) data.
NOTES: Baseline fixed effects are included at the municipality, month, and year in Columns (1) and (2). Baseline fixed effects are included at the municipality and year in Columns (3) and (4). Robust standard errors are clustered at the municipal level. Panel A estimates the difference-in-difference model assuming the occurrence of the earthquakes in 2016. Panel B presents the difference-in-difference model using a linear model. Panel C calculates Oster's bounds, which are presented in brackets. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Difference-in-differences: Earthquakes and Crimes

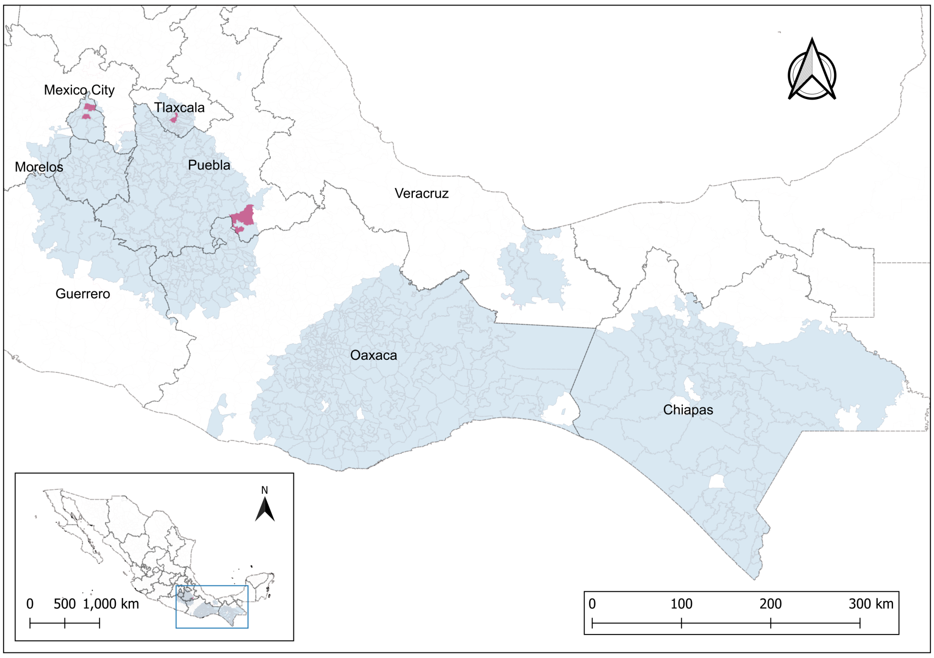
	Homicides	Extortion	Drug Crime	Kidnapping
	(1)	(2)	(3)	(4)
Earthquake	-0.020	0.029*	0.065	0.039***
	(0.026)	(0.016)	(0.054)	(0.012)
R^2	0.54	0.47	0.81	0.21
Observations	51597	51597	51597	51597
Baseline FE	X	X	X	X

SOURCE: National Public Safety System (NPSS)
NOTES: Baseline fixed effects are included at the municipality, month, and year. Robust standard errors are clustered at the municipal level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure I: Municipalities Impacted by the 2017 Earthquakes and Intensity Recorded: Modified Mercalli Scale

SOURCE: CENAPRED.
NOTES: The municipalities affected are classified by the intensity recorded based on the Modified Mercalli scale.

Figure II: Municipalities with Changes in Violence Committed by Local Criminal Organizations



SOURCE: OCVED.