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From Violence to Violence? The Long Term Effects of Conflict on Homicide Rates

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Abstract

This paper studies the long term impact of large scale temporary violence in long term homicide rates. I analyze the case of Guatemala's civil war massacres and assemble data on their locations and homicides between 2016-2019, to test whether there is association between the two. I find that highly victimized municipalities have fewer homicides today. Exploring precipitation variation as an instrument for massacres, I provide evidence that such relation is causal. Generalized trust is also higher in municipalities with more massacres, suggesting a mechanism connecting past violence and present peace through increased local cohesion.

1 Introduction

In this paper, I study the effects of past episodes of great violence on present crime rates of the affected areas. In particular, I exploit variation in massacre locations in 1982 Guatemala to investigate whether they affected later homicide rates.

Central America has some of the highest homicide rates in the world. The region average is 25.9 per 100,000 habitants, much more than Europe (3), Asia (2.3), or Africa (13) (United Nations Office on Drugs and Crime 2019). While this disparity is likely multicausal, the authoritarian and turbulent past has been blamed for part of the high homicide rates of the region(United Nations Office on Drugs and Crime 2007). Guatemala, in particular, has endured a long civil war (1960-1996) where an authoritarian government fought left-wing guerrillas for the control of the country. At its most violent year (1982), its military forces killed thousands of people in indiscriminate massacres as part of an anti-insurgency strategy. Today, the countries' homicide rate (26) is among the highest in the Americas and five times higher than the US equivalent.

Although previous literature has found that early exposure to civil war violence increases the likelihood of criminal behavior later in life (e.g. Miguel et al. (2011)), the impact of such events at the community level did not receive the same attention. Giving that civil war violence was also found to increase local cohesion [1], the net impact of these events is not obvious. On one hand, the initial shock could start a self-reinforcing cycle, where civil war traumatized individuals commit violent crimes and further traumatize new generations. On the other hand, an increase in social capital could reduce the incentives to join gangs and provide mechanisms of conflict resolution.

Since massacres were carried out with the objective of suppressing insurrection, it is plausible that the places targeted were specially capable of organizing collective action, even of the violent kind.[2] If this organizational capacity has any impact of violence, they could bias the results obtained by simple OLS or means comparisons.

The historical record shows other regularities in the perpetration of massacres. In particular, indigenous groups were disproportionately targeted by the government, who though they were helping the guerrilla (CEH 1999). Furthermore, the army revealed a preference to avoid the rain when executing operations, since it decreased its mobility (Ball et al. 1999).[3]

Taking into account the historical record and with the goal to overcome endogeneity concerns, I propose the use of exogenous precipitation as an instrument for massacres. Together with other municipal socioeconomic data collected in the 1981 census, military base locations, 1981 insurgent activities, and cultural markers as controls for pre-existing characteristics, I am able to isolate the massacre's effects in a credible way, avoiding selection bias.

My results indicate that victimized municipalities have 17 homicides (per 100,000 habitants) less in 2016-2019 than they would have otherwise. I also find suggestive evidence that this effect operated through an increase in interpersonal trust. Although unintuitive, this result is in line with the literature on civil conflicts (e.g Bauer et al. 2016) that has found several instances where traumatic events were followed by an increase in social cooperation.

This paper contributes to the literature in two ways. First, it speaks to the body of research studying the impact of violence exposure on crime and related preferences/behaviors. Miguel et al. (2011), Mathieu Couttenier et al. (2019) and Raisa Sara (2020) are the most closely related, as they study the effect of exposure to civil war in later individual crime behavior. The three studies find an increase in the likelihood of later criminal/violent behavior, but do not investigate whether this translates to higher crime rates at an aggregate level. Other research have found that exposure to civil war violence can increase prosocial behavior (Bauer et al. 2016), risk-aversion (Moya 2018)[4], and discount rates (Maarten J. Voors et al. 2012).[5]

[1] Bellows and Miguel (2009) for example find that "Individuals whose households directly experienced more intense war violence are robustly more likely to attend community meetings, more likely to join local political and community groups, and more likely to vote"

[2] Or at least that is what the government believed.

[3] More details on the instrument, and its theoretical and empirical justification, in section 4.

[4] Although Maarten J. Voors et al. (2012) finds otherwise.

[5] Related to this literature in a broader sense, a number of studies have shown an association between serving in the army with later criminal behavior, e.g Galiani et al. (2011) and

Second, it adds to the literature on the causes and consequences of the Guatemalan conflict. In economics, it has not received much attention, with Chamarbagwalaa and Morán (2011) paper showing the deleterious impacts on education being an exception. This being said, the conflict received substantial scrutiny in the political science and historical literature (e.g. Schwartz and Straus 2018, Sullivan 2015, Guberek and Hedstrom 2017, Ball et al. 1999, and Bateson 2017). Although these studies provide both qualitative understanding and valuable data sources for this study (especially Sullivan 2016 and Ball et al. 1999), none of them have attempted to study the nexus between past massacres and present homicide rates.

The remainder of the paper proceeds as follows. Section 2 provides a more detailed background on the Guatemalan conflict and the present context, while section 3 describes the data. Section 4 investigates the relationship between massacres and homicide rates. It presents correlations, instrumental variables estimation strategy and results. Placebos and robustness are in section 5. Section 6 discusses how the massacres affected trust and how this could contribute to the results found in the previous section. Finally, section 7 concludes.

2 Historical Context

2.1 Civil War and Massacres

The first years of the 1960 decade were a turbulent time for Guatemala and its neighbors. Cuba had just experienced the first successful communist revolution in the Americas, and the Guatemalan government was called to help fight against it. General Ydigoras, the president, allowed the United States to use the Guatemalan territory in the training of the forces who would launch the Bay of Pigs invasion against Cuba. This decision triggered the 13 November 1960 revolt of junior military officials that marks the official start of the civil war (Ball et al. 1999).

The conflict would last for 36 years and claim 200,000 lives,[6] with many coups and change of policy in between. It would also evolve from a limited dispute among urban middle classes in its beginning (Ball et al. 1999), to a conflict violent enough to warrant the first condemnation of genocide by a court in the country of the accused.[7]

Starting in the 1970 decade, but growing faster in the final years of it, guerrilla groups like the EGP (Ejército Guerrillero de los Pobres/Guerrilla Army of the Poor) started to recruit the rural population to its ranks. The group's forces

Cesur and Sabia (2016). Mattina (2017) finds that the Rwandan Genocide increased domestic violence against women who married after it. However, the main mechanism is skewed sex ratios, not trauma.

[6] This is the most widely cited number from Memoria Histórica (1998). CEH (1999) restricts its estimation of the total of victims to the 1978-1996 period, reporting 132,000 deaths.

[7] In 2013, Efrain Rios Montt was sentenced to 80 years in prison because of genocide and crimes against humanity. He had been the country's president between March 1982 and August 1983. His sentence would be overturned 10 days latter.

grew in both controlled area and number of recruits (CEH 1999). Frustrated by the hit-and-run tactics of the guerrilla and the use it made of the local population support to conceal their location and operations, the army decided to attack entire villages.[8]

On November 1981, Operation Ashes(Ball et al. 1999) would start the bloodiest period of the Guatemalan Civil War. The military attacked (mostly Maya) villages where guerrillas were suspected to hide. These operations involved not only killings, but also rapes, beatings, and destruction of crops, buildings and other types of physical capital. The attacks would continue and intensify under General Rios Montt. At the cost of thousand of deaths, the guerrillas were mostly defeated, and the conflict became much less intense in its following years.[9]

The return to democracy in 1986, the end of the Cold War and the pressure from the international community incentivized the government and the remaining fighting groups to sign a peace deal, ending the civil war in 1996.

Figures 1 and 2 show the temporal evolution of killings. As previously stated, 1982 was abnormally violent, and the rural areas suffered the heavier toll. In that year, the number of killings was 200 times bigger than the other years' average, with an implied homicide rate of 201 (per 100,000 population). This is 40 times the US equivalent (United Nations Office on Drugs and Crime 2020) considers only deaths from the conflict, and does not account for unreported cases.

2.2 Post-conflict violence in Guatemala

Guatemala has been a violent country for decades. On the post-conflict period, homicide rates have been consistently above 20 per 100,000 population at the national level (United Nations Office on Drugs and Crime 2020). In 2009, this number reached 45 per 100,000.

Geographically, homicides are more prevalent in the coastal areas, the border with Honduras, El Salvador and part of the border with Mexico.[10] This pattern is sometimes attributed to the role of Guatemala in international drug trade routes (e.g. Crisis Group (2014)). However, the large western border area with Mexico is mostly free of homicides, presenting a puzzle to this theory.

Guatemalan gangs and criminal organizations are known to collaborate with Mexican cartels (Brands 2010).[11] These groups also engage in human trafficking, extortion, protection rackets and other activities where territorial control is of

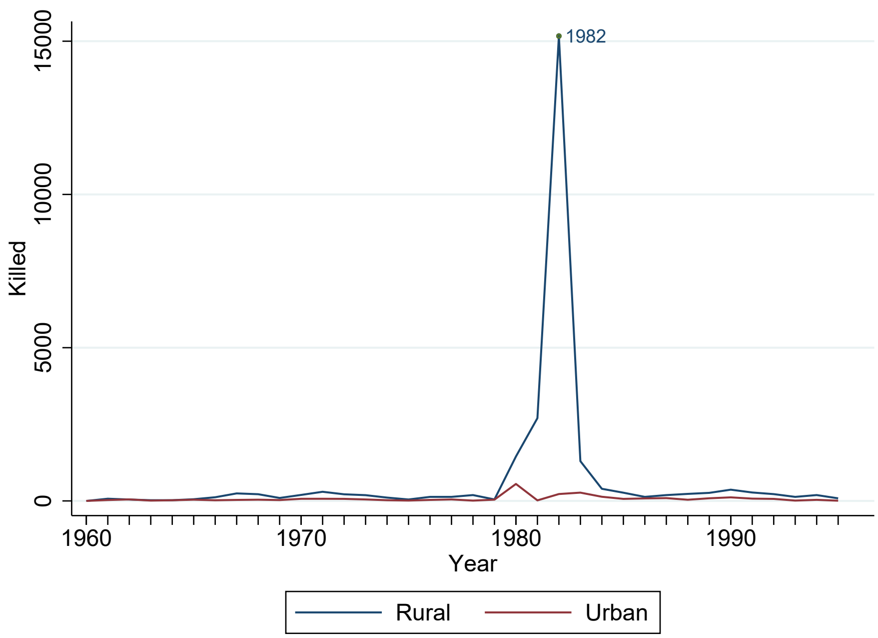
[8]The army doctrine referred to this as "draining the ocean" or "quitting the fish's water". This was a reaction to the Maoist principle that the guerrilla should interact with the people as the fish interact with the water (CEH 1999).

[9]48% of the conflict human right's violations happened in 1982, according to CEH (1999)

[10]More details in section 3.

[11]Current and former state actors also do this(Brands 2010). Among the most disturbing examples, is the case of Kaibiles, a Guatemalan elite military force regularly called to help with the repression of the drug trade (Brands 2010). In the past, the Kaibiles were connected with civil war massacres. More recently, former members worked for the Zetas (Evans and Franzblau 2013), a Mexican criminal group that who originated from former Mexican military.

Figure 1: Registered Killings per Year



Notes: Data from Ball (1999). Include the categories: "Killed", and "Disappeared, latter found killed"

particular importance (Brands 2010). This motivates occasional battles for territory.

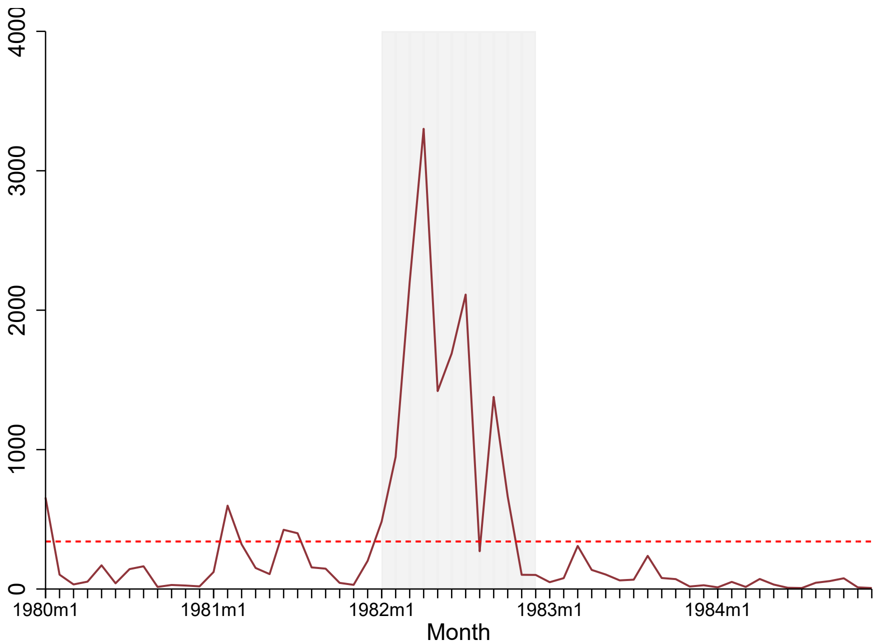
Organized groups are regularly blamed for Guatemala's homicide problem (Cruz et al. 2020). Although the precise number is unknown, estimates have pointed that criminal groups[12] are responsible for a share of about 40% (Dudley 2016) of homicides in some neighborhoods at the capital.[13] When surveyed (Cruz et al. 2020) about the reasons they joined gangs, former members regularly mention a search for community and respect. Economic motivations are also common, but not as prevalent.[14] Winton (2006) survey with young people (not selected by gang membership) provides a similar picture. The evidence in both studies is mostly based on qualitative interpretation of survey answers and

[12] MS-13, Barrio 18 and many other smaller (and sometimes subordinate) gangs.

[13] More specifically, Dudley (2016) study Zone 18 in Guatemala city.

[14] "(...) most community stakeholders and former gang members interviewed mentioned family disintegration; yearning for respect; and the need for protection, affection, and belonging as the most important factors that drive youth to join gangs. Although more than 60 percent of the former gang members interviewed cited lack of bonding or family dysfunction as a reason for joining gangs, less than 15 percent mentioned the search for material resources or income."(Cruz et al. 2020)

Figure 2: Registered Rural Killings per Month



Notes: The red dashed line shows the period average (1980-1985). Data from Ball (1999). Include the categories: "Killed", and "Disappeared, latter found killed".

quantitative analysis supported by small samples. Nonetheless, they suggest the relevance of social capital in determining gang recruitment.

3 Data and Descriptive Statistics

I assembled information from a variety of sources to construct a dataset of Guatemalan municipalities, their exposure to civil-war conflict, precipitation levels at the time, present homicide rates, and relevant control variables. In this section, I briefly discuss data sources, construction, and general patterns. A more detailed and case by case description can be found in the appendix.

Measures of exposure to civil war conflict, massacres and confrontations, were derived from Sullivan (2016) data. Massacres are defined as "the execution of five or more people, in the same place, as part of the same operation and whose victims were in an indefensible state."(Mezquita, Rocio 2000). Confrontations [15] include violent and peaceful disputes and "are operationalized as public efforts

[15] Originally named "Overt, collective challenges".

by organized challengers to press claims against political authority. Examples include strikes, demonstrations, marches, roadblocks, targeted killings, arson, kidnapping, and the taking of hostages." (Sullivan 2016).

I use Sullivan (2016) monthly counts of massacres and confrontations at the municipal level, aggregate these counts for 1982 and normalize them by population.[16] The resulting variables, massacres and confrontations rate, are the main measures of conflict used throughout this paper.

Figure 3 displays the geographical distribution of massacres. Massacres are concentrated in the center and northwest of the country, coinciding with historically indigenous and less developed areas.

I use police data (Policia Nacional Civil) as a source for homicides. **Homicide rates** are constructed by dividing the number of victims by the 2018 population, and multiplying the result by 100,000. As some municipalities are very small and do not register murders all years, I use the average between 2016-2019 homicide rates for most estimations.

Figure 4 shows the spatial distribution of this variable in the sample. Homicides have the opposite pattern of massacres. The center and northwest of the country have remarkably low rates, comparable to developed countries and less than half the ones registered in the United States (5 according to United Nations Office on Drugs and Crime 2020) while some areas report very high homicide rates.

The data for the precipitation-based instrument comes from World Clim.[17]. To convert this data from the pixel level to the municipality level, I take a weighted average of pixels whose areas intersect those of the municipalities. The weights correspond to the share each pixel has of the municipality area. [18]

The variable Precipitation (1982) is the sum of monthly municipal precipitation at the height of conflict, 1982. Similarly, Precipitation (1961-2018) measures the mean of this annual sum, between 1961 and 2018 and serves as a control for characteristics correlated with the historical level of rain.

Finally, other control variables were gathered from sources like the Guatemalan Census (1981 and 2018), satellite data, previous literature, commissions of truth, and surveys of public opinion. More details can be found in the appendix.

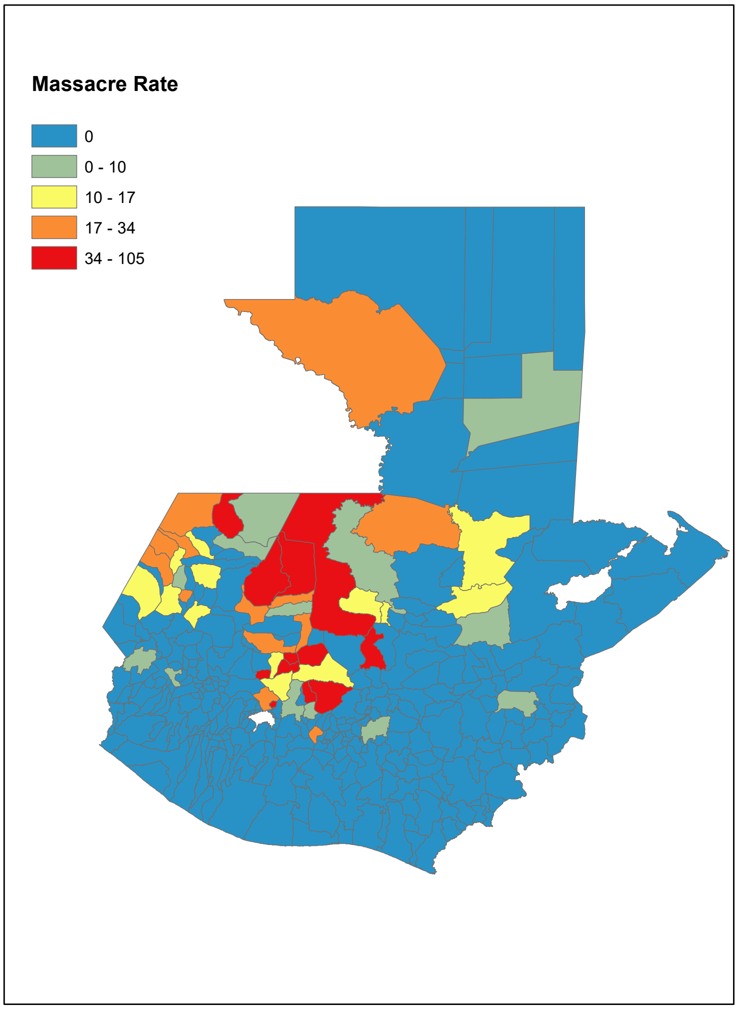
Table 1 shows some key variable's means, and how they differ between victimized (by massacres) and non-victimized areas. Victimized municipalities were more indigenous and less literate. Their average population was higher, but this is largely driven by the capital city. Today, these municipalities have fewer homicides and are less urban. Massacred municipalities also register higher generalized trust and lower trust in the military.

[16] I divide the counts by 1981 (last census date) population and multiply the resulting number by 100,000.

[17] Harris et al. (2013) and Fick and Hijmans (2017)

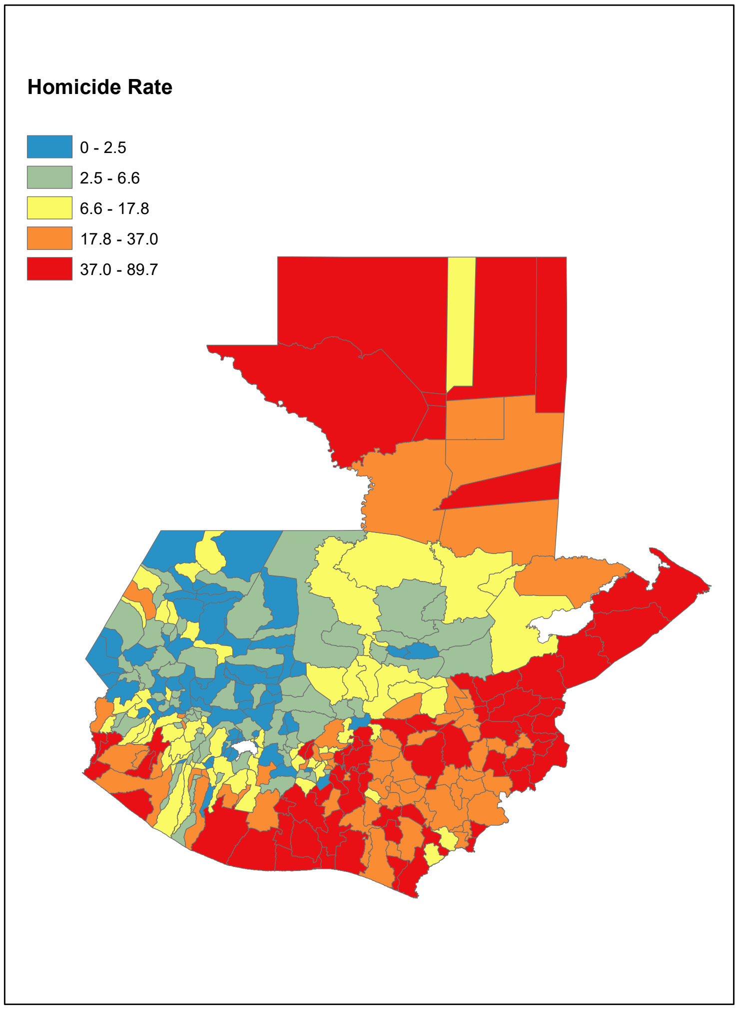
[18] More formally: $P_{it} = \sum_{j=1}^{J} \frac{A_{ij}}{A_i} P_{jt}$. Where A_{ij} is the size of the area of municipality i covered by pixel j and P_{jt} is the precipitation in pixel j, time t. P_{it} is the corresponding municipality level precipitation.

Figure 3: Massacres (1982)



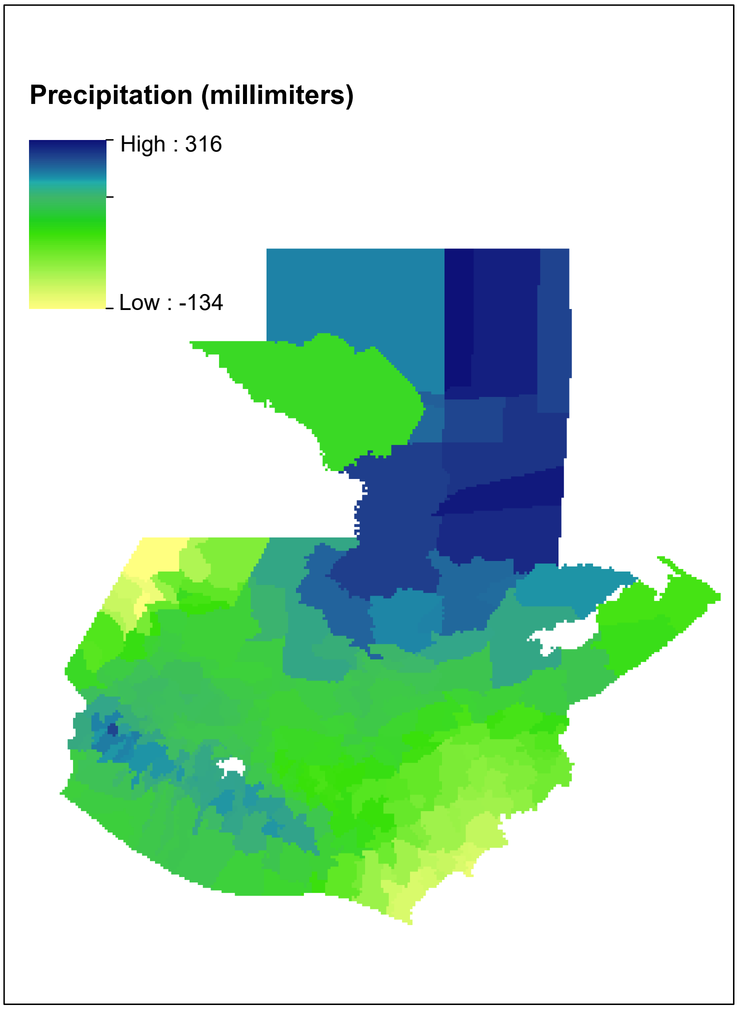
Notes: Massacre counts and 1981 population from Sullivan (2016). Massacres are defined as the execution of of five or more people in an indefensible state. Massacre Rate is the count of massacres in 1982, divided by 1981 population and multiplied by 100,000. Each interval including positive values is a quartile of the distribution of (positive) massacre rates.

Figure 4: Average yearly Homicide rate per 100,000 population (2016-2019)



Notes: Data on victims is from the "Policia Nacional Civil", extracted from Guatemala's National Institute of Statistics(INE in the Spanish acronym). The rates were calculated dividing the number of victims by the 2018 population data and multiplying the result by 100,000. The rates are relative to the 4 year period of 2016-2019, instead of the more usual 1 year period. Each interval in the map represent one quintile of the distribution of homicide rates.

Figure 5: Excess Precipitation (1982)



Notes: Pixel-level data from World Clim. Excess precipitation measures the difference between average monthly precipitation in 1982, and the average monthly precipitation between 1961-2018.

Table 1: Summary Statistics

	At least one massacre Mean	No massacre Mean
Baseline		
Share Indigenous (1981)	.76	.46
Share Literate (1981)	.36	.53
Population (1981)	35,258	15,540
Ruggedness	3.1	2.7
Elevation (meters)	1,592	1,307
Precipitation (1961-2018)	2.2	2
Precipitation (1982)	2.3	2.1
Conflict		
Massacre Rate (1982)	26	0
Massacre Events (1982)	4.7	0
Confrontations Rate (1981)	9.6	6.5
Modern		
Homicide Rate (2016-2019)	8.5	22
Share Imigrant from Massacred Mun.(2018)	.033	.042
Share Imigrant (2018)	.095	.18
Share Male (2018)	.48	.49
Share Young (2018)	.3	.3
Share Urban (2018)	.34	.45
Generalized Trust	26	21
Trust in the Military	31	34
Observations	51	274

Notes: Population, migration, share Indian and share literate data from the Guatemalan Census. The 1973 and 1981 data was collected in Sullivan (2016). Massacres and confrontation counts from Sullivan (2016). Rates obtained by aggregating cases, dividing by 1981 population and multiplicating by 100,000. Massacre rates calculated for 1982, confront rates calculated for 1981. Precipitation data from Funk et al. (2014) and is measured in mililiters. Elevation and ruggedness calculated using data from Earth Resources Observation and Science Center (1997). Homicide Rate refers to the average of the 2016-2019 period. For each year, the number of victims is aggregated, divided by 2018 population and multiplied by 100,000. The count of Homicides comes from Police Data. Share urban, male, imigrant, imigrant from massacred municipalities, and young calculated with data from the 2018 Guatemalan Census. Trust variables from Latinobarometro.

4 Massacres and Homicides

4.1 The correlation between Massacres and Homicide Rates

I start the investigation of persistent effects of massacres by estimating correlations in the data. This is done by regressing homicide rates (averaged between 2016-2019) by 1982 massacre rates.

As can be seen in tables 2 and 3, areas that suffered more massacres have fewer homicides today. This relation is true even controlling by demographic, geographic, or conflict-related variables.

Table 2: Massacres and Homicide Rates: OLS regressions

	Homicide Rate	Homicide Rate	Homicide Rate	Homicide Rate
Massacre Rate	-0.32	-0.33	-0.28	-0.23
	(0.07)***	(0.07)***	(0.07)***	(0.04)***
Military Base	N	Y	N	N
Ruggedness	N	N	Y	N
Elevation	N	N	N	Y
N	325	325	325	325

Notes: Coefficients estimated by OLS. All regressions include a constant. Conley standard errors in parenthesis, error correlation allowed up to 2.5 degrees difference in latitude and longitude (approximately 278km at Guatemala's latitude).

*p<0.10, ** p<0.05, *** p<0.01

4.2 Instrumental Variables Strategy and Results

Although the correlation between massacres and homicide rates are significant, they do not imply causality in the absence of strong assumptions about the process that led to the massacres. In order to estimate causal effects, I employ a two stage least squares with precipitation as an instrument for massacres.

The identification rests in two assumptions. First, that rain is an impeditive to repressive state actions so that the armed forces refrained attacking some places because of the rain. Second, that conditional on the control variables, 1982 precipitation does not affect current crime through any other channel.

Above normal precipitation could stop a massacre in at least two ways. One, heavy rain or muddy roads can make the army initially postpone an attack, waiting for a better time, or carry it on at a slower rate. If the political scenario changes before an alignment of the proper operation conditions, the target location could be spared. Given that most of the massacres happened within a

Table 3: Massacres and Homicide Rates: OLS regressions

	Homicide Rate	Homicide Rate	Homicide Rate	Homicide Rate
Massacre Rate	-0.08	-0.11	-0.31	-0.16
	(0.02)***	(0.05)**	(0.06)***	(0.03)***
Share Indigenous (1981)	Y	N	N	N
Literacy (1981)	N	Y	N	N
Confrontations Rate (1981)	N	N	Y	N
Minority Language (1981)	N	N	N	Y
N	325	325	325	325

Notes: Coefficients estimated by OLS. All regressions include a constant. Conley standard errors in parenthesis, error correlation allowed up to 2.5 degrees difference in latitude and longitude (approximately 278km at Guatemala's latitude).

*p<0.10, ** p<0.05, *** p<0.01

year, an unusually rainy weather in 1982 could be the difference between being attacked or not.

Alternatively, the postponement of an attack could give villages the time to know the consequences of collaborating with the guerrillas or going against the government wishes. Motivated by fear, some of them may decide to side with the military, in order to avoid any confrontation.

These theoretical justifications are supported by historic evidence. Ball et al. (1999), for example, reports that the army waited for the summer to attack villages distant from their bases in 1981, in the humid region of Ixil. Had it rained more there, the attack could have been postponed further or reached fewer villages. As an illustration of the seasonality of attacks, figure 6 aggregate rural killings by month of the year. The killings increase with the progression of the dry season, and then decline as the rain season goes on (May to October) and is followed by end of the year festivities. Furthermore, Operation Sofia (part of a counter-insurgency campaign that massacred indigenous) documents (digitized by Schwartz and Straus 2018) also contain repeated complaints about how the rain created difficulties. Additional evidence in favor of the proposed instrument is provided in section 4.3 by placebo studies.

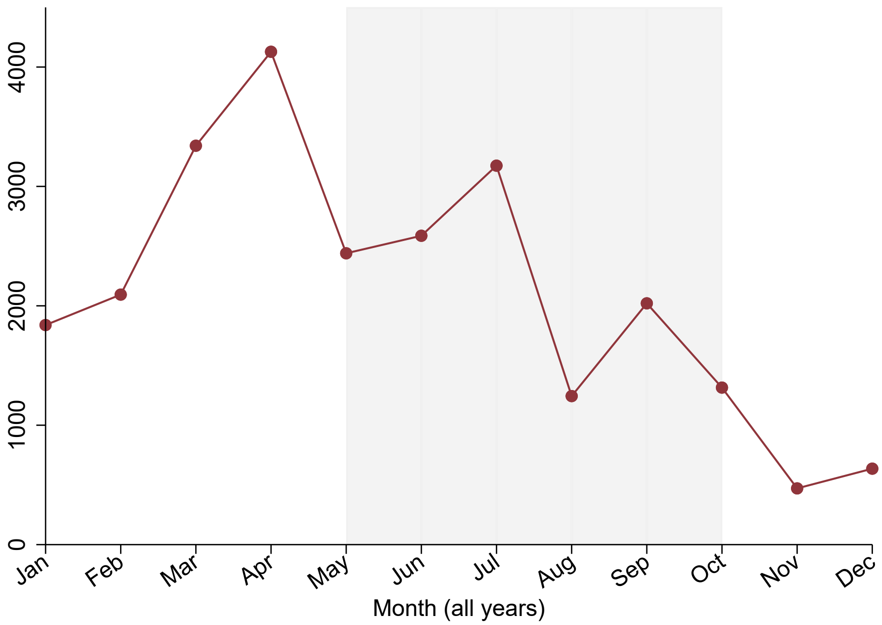
I estimate the following regressions by 2SLS:

$$Massacre_i = \alpha_0+\alpha_1 Precipitation(1982)_i+\alpha_2 Precipitation(1961-1981)_i+\alpha_3 X_i+e_i \quad (1)$$

$$Homicide_i = \beta_0+\beta_1 \widehat{Massacre}_i+\beta_2 Precipitation(1961-1981)_i+\beta_3 X_i+u_i \quad (2)$$

$Homicide_i$ is the homicide rate municipality i had between 2016-2019. $Massacre_i$

Figure 6: Rural Killings and Seasonality



Notes: Data from Ball (1999). Include the categories: "Killed", and "Disappeared, latter found killed".

is the massacre rate in 1982, the height of the conflict. X_i is a vector of controls that includes share of indigenous population (in 1981), literacy (in 1981) rebel activities (confront rate) in the year before (1981), presence of a military or police base, elevation, ruggedness and a dummy measuring whether i is in a minority language area or not. $Precipitation(1982)_i$ is the precipitation in 1982, while $Precipitation(1961-1981)_i$ is the average precipitation between 1961-1981. In some regressions, I include modern controls as an additional test. Since these are arguably bad controls[19] the preferred estimations do not use them, even though they generally do not change results. Modern controls are the share of men, young (15-19 years old), urban, immigrants, and immigrants *from victimized municipalities.* The later two variables in particular are intended to address possible spillover effects from the massacres.[20]

Table 4 reports the reduced form results. The coefficient is positive and

[19]Massacres could have impacted them.

[20]Although it should be noticed that most of the displaced population later returned either to their origin villages or close settlements (CEH 1999), so this should not be a big worry. Moreover, municipalities that experienced a massacre have a lower share of their native-born population living in other municipalities.

significant for all but one specification (column 1 without any controls other than average precipitation). 0.1 ml of precipitation translates to an increase of 3.1 in the 2016-2019 homicide rates in the 2016-2019 period according to the preferred specification (column 4). 24% of the sample had its 1982 precipitation exceeding its average levels by more than 0.1 ml.

Table 4: Reduced Form: The effect of Precipitation on Homicide Rates

	(1)	(2)	(3)	(4)	(5)
Precipitation	-7.125	19.107	34.878	30.968	29.344
	(53.292)	(11.632)	(7.513)***	(7.844)***	(7.873)***
Average Precipitation (1961-1981)	Y	Y	Y	Y	Y
Geographic Controls	N	Y	Y	Y	Y
Demographic Controls	N	N	Y	Y	Y
Conflict Controls	N	N	N	Y	Y
Modern Controls	N	N	N	N	Y
N	325	325	325	325	325

Notes: All regressions include average precipitation from 1961 to 1981. Geographic controls include ruggedness and elevation. Demographic controls are the share of indigenous in 1981, share literate in 1981 and a minority language dummy. Conflict controls are base presence and confrontations rate. Finally, modern controls include: urban population share, share aged 15-19, share male, share of imigrants and share of imigrants from massacred municipalities. Conley standard errors in parenthesis, error correlation allowed up to 2.5 degrees difference in latitude and longitude (approximately 278km at Guatemala's latitude).

*p<0.10, ** p<0.05, *** p<0.01

Table 5 report the main results, with the first stage at panel (a), and the IV coefficients at panel (b). Precipitation have consistently negative effect on massacres, with a 0.1 ml extra precipitation being associated with a decrease of 5 in the massacre rate. The IV results also point to a decreasing effect of massacres on homicides. The estimated coefficient is negative in four out of five specifications, the with historical precipitation as the only control is the sole exception. The massacre rate mean, among the municipalities with any massacre at all, was 26 (per 100,000 population). The coefficients in the preferred specification imply that going from a massacre rate of 0 (the mode) to 26 would result in a decrease of 17 in homicide rates (per 100,000 population). This is slightly more than the difference between massacred and non-massacred municipalities (13.5). The inclusion of modern controls does not change this much (the coefficient is only 15% smaller).

Another way to evaluate the practical significance of the estimated effects is to compare it with homicide rates in Guatemala and abroad. The 17 decrease is equivalent to 76% of the 2018 Guatemala's countrywide homicide rate (22.5), and 340% of the 2018 US homicide rate (5).

Table 5: Instrumental Variables Estimation

(a) First Stage: The effect of Precipitation on Massacres

	(1)	(2)	(3)	(4)	(5)
Precipitation	-34.832	-39.726	-41.490	-48.065	-51.452
	(17.835)*	(18.706)**	(12.999)***	(13.558)***	(12.228)***
Average Precipitation (1961-1981)	Y	Y	Y	Y	Y
Geographic Controls	N	Y	Y	Y	Y
Demographic Controls	N	N	Y	Y	Y
Conflict Controls	N	N	N	Y	Y
Modern Controls	N	N	N	N	Y
F	4	5	10	13	18
N	325	325	325	325	325

(b) The effect of Massacres on Homicide Rates(2016-2019)

	(1)	(2)	(3)	(4)	(5)
Massacre Rate	0.205	-0.481	-0.841	-0.644	-0.519
	(1.568)	(0.192)**	(0.354)**	(0.241)***	(0.189)***
Average Precipitation (1961-1981)	Y	Y	Y	Y	Y
Geographic Controls	N	Y	Y	Y	Y
Demographic Controls	N	N	Y	Y	Y
Conflict Controls	N	N	N	Y	Y
Modern Controls	N	N	N	N	Y
N	325	325	325	325	325

Notes: All regressions include average precipitation from 1961 to 1981. Geographic controls include ruggedness and elevation. Demographic controls are the share of indigenous in 1981, share literate in 1981 and a minority language dummy. Conflict controls are base presence and confrontations rate. Finally, modern controls include: urban population share, share aged 15-19, share male, share of imigrants and share of imigrants from massacred municipalities. Conley standard errors in parenthesis, error correlation allowed up to 2.5 degrees difference in latitude and longitude (approximately 278km at Guatemala's latitude).

*p<0.10, ** p<0.05, *** p<0.01

5 Placebos and Robustness

In this section, I provide complementary evidence in favor of the identification strategy proposed in section 4. First, I perform a number of placebo studies to test the mechanisms connecting precipitation and massacres. Second, I vary some previously made specification choices and show that the main results are robust to these changes.

5.1 Placebos

The IV strategy employed in the last section relies on in the assumption that massacres were motivated by political challenges, but deterred by logistical costs associated with precipitation. If this story is right, it should be expected that massacres were more responsive to precipitation under some particular conditions. In this subsection, I split the sample in a number of ways in order to test whether precipitation effects on massacres (as measured by equation 1) vary in a way consistent with my assumptions.

First, it should matter whether the municipality was hosting rural guerrillas. The absence of guerrillas would imply that the attack is strategically irrelevant for the regime stability, so that it should not occur regardless of weather conditions. The first placebo study divides the country according to the presence of rural guerrillas. Using data from Sharp (2017), I consider departments without any EGP fronts as without rural guerrillas. To this group, I add the departments of Petén and Guatemala. For Petén, its guerrilla occupied area is very small and covers only a (small) fraction of one municipality without any massacre. In the case of the capital department, being more urbanized and closer to power makes the occurrence of rain a lesser problem for military activities. The departments with an EGP front (except for Petén and Guatemala) are considered as having rural guerrilla. (table 6 test the first hypothesis).

As a variation of the same idea, I perform another placebo test using a more fine-grained measure of political confrontation[21] from Sullivan (2016). Municipalities were divided according to the occurrence of at least one peaceful or violent confrontation against the government in 1981 (table 7).

Second, the presence of a military base should attenuate the relevance of precipitation, since the logistical challenges created by the rain would be diminished. To test this assumption, the third placebo divides the municipalities according to the presence of a military base (table 8, data from Sullivan 2016).

Dividing the country by the presence of Rural Guerrilla (table 6), I find that the effect of precipitation is six times stronger in departments where they were present. This being said, there is still a small (but statistically significant) effect even in departments without my measure of Rural Guerrilla. This can be attributed to inaccuracies in this measure of their presence,[22] mistakes by the government and even goals other than political repression by their part.

[21] Originally named as Overt, collective challenges

[22] I use EGP presence, but other groups may have operated in other parts of the national territory.

Dividing the country by confrontations (table 7) also did not change the main conclusion. As expected, the impact of precipitation is (almost two times) bigger in places where there were recent confrontations.

Finally, table 8, shows evidence of the relevance precipitation had in areas without a military base. Areas with bases do not seem to be as affected, although the small sample size should make these results to be taken with caution.

Table 6: Precipitation and massacres, sample restricted by presence of rural guerrilla

	Massacre Rate	Massacre Rate
Precipitation	-61.05	-14.42
	(7.79)***	(8.40)*
Average Precipitation (1961-1981)	Y	Y
Geographic Controls	Y	Y
Demographic Controls	Y	Y
Conflict Controls	Y	Y
Sample Restriction	Rural Guerrilla	No Rural Guerrilla
N	136	189

Notes: All regressions include average precipitation from 1961 to 1981. Geographic controls include ruggedness and elevation. Demographic controls are the share of indigenous in 1981, share literate in 1981 and a minority language dummy. Conflict controls are base presence and confrontations rate. Finally, modern controls include: urban population share, share aged 15-19, share male, share of imigrants and share of imigrants from massacred municipalities "Rural Guerrila" consider free from rural guerrila the departments without any EGP fronts, and the departments of Petén and Guatemala. Conley standard errors in parenthesis, error correlation allowed up to 2.5 degrees difference in latitude and longitude (approximately 278km at Guatemala's latitude).

*p<0.10, ** p<0.05, *** p<0.01

5.2 Robustness

Pre-conflict controls

In the main results (table 5), conflict time controls include share indigenous and share literate, as measured by the 1981 census. However, it is possible that massacres may have influenced these variables, making them bad controls. In 1981, violence was already climbing, and the first massacres were happening, even if in a smaller scale. Therefore, it is possible that these events, and the expectation of more attacks, could impact the census results in a number of

Table 7: Precipitation and massacres, sample restricted by presence by 1981 confrontations

	Massacre Rate	Massacre Rate
Precipitation	-65.50	-37.92
	(12.89)***	(15.09)**
Average Precipitation (1961-1981)	Y	Y
Geographic Controls	Y	Y
Demographic Controls	Y	Y
Conflict Controls	Y	Y
Sample Restriction	At Least One Confrontation	No Confrontation
N	120	205

Notes: All regressions include average precipitation from 1961 to 1981. Geographic controls include ruggedness and elevation. Demographic controls are the share of indigenous in 1981, share literate in 1981 and a minority language dummy. Conflict controls are base presence and confrontations rate. Finally, modern controls include: urban population share, share aged 15-19, share male, share of imigrants and share of imigrants from massacred municipalities "confrontations" divide the sample in municipalities with and without overt challenges against the government authority. Conley standard errors in parenthesis, error correlation allowed up to 2.5 degrees difference in latitude and longitude (approximately 278km at Guatemala's latitude).

*p<0.10, ** p<0.05, *** p<0.01

ways. First, it could make the population less wiling to answer census workers. Second, it could incentivize them to mislead census workers, in order to avoid being targeted because of indigenous origins. Third, it could make part of the population flee their towns of origin in the anticipation of violence.

Considering this, I re-estimate the regressions but using instead the share of indigenous and share literate measured in the 1973 census, instead of 1981. Table 9 display the results. For both the first and second stage, the coefficients are virtually unchanged. In the preferred specification, the estimated effect of a unit increase in the massacre rate is a 0.61 decrease in the homicide rate.

2019 homicides

Homicide rates are, by definition, bounded below by zero. At the same time, a municipality with a small population, like many in Guatemala, can have very high homicide rates following a single death. As a result, the municipal homicide rates sample has both high variance (in the time series and cross-section) and many zeroes. Considering this, all estimations up to this point used the 2016-

Table 8: Precipitation and massacres, sample restricted by presence of Military base

	Massacre Rate	Massacre Rate
Precipitation	-27.58	-50.38
	(21.38)	(14.96)***
Average Precipitation (1961-1981)	Y	Y
Geographic Controls	Y	Y
Demographic Controls	Y	Y
Conflict Controls	Y	Y
Sample Restriction	Military Base	No Military Base
N	26	299

Notes: All regressions include average precipitation from 1961 to 1981. Geographic controls include ruggedness and elevation. Demographic controls are the share of indigenous in 1981, share literate in 1981 and a minority language dummy. Conflict controls are base presence and confrontations rate. Finally, modern controls include: urban population share, share aged 15-19, share male, share of imigrants and share of imigrants from massacred municipalities "Bases" divide the sample regarding the presence of a military base in the municipality. Conley standard errors in parenthesis, error correlation allowed up to 2.5 degrees difference in latitude and longitude (approximately 278km at Guatemala's latitude).

*p<0.10, ** p<0.05, *** p<0.01

2019 average homicide rates as a measure of violence.

Although justifiable, the choice of a 4-year average is arguably not the most natural one. In this subsection, I test whether the main results are dependent on this choice by employing 2019 homicide rates as the dependent variable

Table 10 has the results. The coefficients change little. While the preferred specification (displayed in table 5, column 4) result in a coefficient of -0.64, its counterpart with 2019 homicide rates is -0.7.

Alternative measures of Massacres

Throughout all this paper, I have used massacre rates as a measure of the intensity of civil-war violence each municipality has endured. The underlying assumption of this choice is that massacre-related effects scale linearly with the count of massacres, but its effected is diluted by the population. In other words, a municipality with 2 massacres and 10,000 inhabitants (massacre rate = 20), is considered as affected as a municipality with one massacre and 5,000 population.

Different plausible assumptions would imply different choices. Suppose, for example, that most of the population from any targeted municipality is not directly affected by massacres. Then, much of the impact will come from a sense of vulnerability. It is likely that this sense will grow with the number of massacres, but it is not a given that villagers would divide this count by census population when estimating how at risk they were. News availability and an intuitive sense of how frequent massacres were within each individual's network can be used to justify *some* adjustment by population, but not necessarily in the way chosen. In the extreme case of perfect information on massacres and no will or necessary knowledge to consider population when assessing risks, the count of massacres could arguably be a better measure of impact than its rate.

Similarly, it may be the case that one massacre is enough to scare and traumatize the entire municipal population, with further events having small marginal impact. In this case, a dummy for massacre occurrence would be the best measure of violence intensity.

Tables 11 and 12 test whether the main results are robust to different measures of massacre intensity. The estimated impact of each massacre occurrence is a reduction of 4.31 in the homicide rate. Among municipalities with at least one massacre, the average count was 4.7. Employing the same logic used for the main results, this implies that the average affected municipality has a 20 smaller homicide rate than it would have otherwise. Likewise, the estimated effect of the massacre dummy is -18 in the preferred specification.[23] When compared with the same metric, both results are similar, albeit higher, to the 18 decrease in homicide rates found in the main estimation.

[23]Note however that this effect is sometimes non-significant (albeit always negative) in some specifications. The first stage's F-statistic is also small. Estimations of the effect of the massacre dummy on homicide rates should be taken with a grain of salt.

Table 9: IV results, percent literate and percent indigenous from 1973 census

(a) First Stage: The effect of Precipitation on Massacres

	(1)	(2)	(3)	(4)	(5)
Precipitation	-34.832	-39.726	-38.908	-44.865	-48.857
	(17.835)*	(18.706)**	(13.736)***	(14.348)***	(12.334)***
Average Precipitation (1961-1981)	Y	Y	Y	Y	Y
Geographic Controls	N	Y	Y	Y	Y
Demographic Controls	N	N	Y	Y	Y
Conflict Controls	N	N	N	Y	Y
Modern Controls	N	N	N	N	Y
F	4	5	8	10	16
N	325	325	325	325	325

(b) The effect of Massacres on Homicide Rates(2016-2019)

	(1)	(2)	(3)	(4)	(5)
Massacre Rate	0.205	-0.481	-0.796	-0.610	-0.540
	(1.568)	(0.192)**	(0.364)**	(0.252)**	(0.210)**
Average Precipitation (1961-1981)	Y	Y	Y	Y	Y
Geographic Controls	N	Y	Y	Y	Y
Demographic Controls	N	N	Y	Y	Y
Conflict Controls	N	N	N	Y	Y
Modern Controls	N	N	N	N	Y
N	325	325	325	325	325

Notes:All regressions include average precipitation from 1961 to 1981. Geographic controls include ruggedness and elevation. Demographic controls are the share of indigenous in 1973, share literate in 1973 and a minority language dummy. Conflict controls are base presence and confrontations rate. Finally, modern controls include: urban population share, share aged 15-19, share male, share of imigrants and share of imigrants from massacred municipalities. Conley standard errors in parenthesis, error correlation allowed up to 2.5 degrees difference in latitude and longitude (approximately 278km at Guatemala's latitude). *p<0.10, ** p<0.05, *** p<0.01

Table 10: The effect of Massacres on 2019 Homicide Rates

	(1)	(2)	(3)	(4)	(5)
Massacre Rate	0.182	-0.462	-0.825	-0.705	-0.702
	(1.235)	(0.293)	(0.333)**	(0.270)***	(0.248)***
Average Precipitation (1961-1981)	Y	Y	Y	Y	Y
Geographic Controls	N	Y	Y	Y	Y
Demographic Controls	N	N	Y	Y	Y
Conflict Controls	N	N	N	Y	Y
Modern Controls	N	N	N	N	Y
N	325	325	325	325	325

Notes:All regressions include average precipitation from 1961 to 1981. Geographic controls include ruggedness and elevation. Demographic controls are the share of indigenous in 1981, share literate in 1981 and a minority language dummy. Conflict controls are base presence and confrontations rate. Finally, modern controls include: urban population share, share aged 15-19, share male, share of imigrants and share of imigrants from massacred municipalities The first stage is not shown, as it is, by definition, equal to table 5 results. Conley standard errors in parenthesis, error correlation allowed up to 2.5 degrees difference in latitude and longitude (approximately 278km at Guatemala's latitude).

*p<0.10, ** p<0.05, *** p<0.01

Table 11: Instrumental Variables Estimation

(a) First Stage: The effect of Precipitation on Massacres

	(1)	(2)	(3)	(4)	(5)
Precipitation	-4.292	-4.835	-5.155	-7.185	-7.608
	(2.655)	(2.579)*	(1.694)***	(1.999)***	(2.010)***
Average Precipitation (1961-1981)	Y	Y	Y	Y	Y
Geographic Controls	N	Y	Y	Y	Y
Demographic Controls	N	N	Y	Y	Y
Conflict Controls	N	N	N	Y	Y
Modern Controls	N	N	N	N	Y
F	3	4	9	13	14
N	325	325	325	325	325

(b) The effect of Massacres on Homicide Rates(2016-2019)

	(1)	(2)	(3)	(4)	(5)
Massacre Events	1.660	-3.952	-6.765	-4.310	-3.511
	(12.888)	(1.630)**	(2.932)**	(1.653)***	(1.592)**
Average Precipitation (1961-1981)	Y	Y	Y	Y	Y
Geographic Controls	N	Y	Y	Y	Y
Demographic Controls	N	N	Y	Y	Y
Conflict Controls	N	N	N	Y	Y
Modern Controls	N	N	N	N	Y
N	325	325	325	325	325

Notes: All regressions include average precipitation from 1961 to 1981. Geographic controls include ruggedness and elevation. Demographic controls are the share of indigenous in 1981, share literate in 1981 and a minority language dummy. Conflict controls are base presence and confrontations rate. Finally, modern controls include: urban population share, share aged 15-19, share male, share of imigrants and share of imigrants from massacred municipalities. Conley standard errors in parenthesis, error correlation allowed up to 2.5 degrees difference in latitude and longitude (approximately 278km at Guatemala's latitude).

*p<0.10, ** p<0.05, *** p<0.01

Table 12: Instrumental Variables Estimation

(a) First Stage: The effect of Precipitation on Massacres

	(1)	(2)	(3)	(4)	(5)
Precipitation	-1.189	-1.332	-1.451	-1.725	-1.721
	(0.934)	(0.971)	(0.815)*	(0.795)**	(0.754)**
Average Precipitation (1961-1981)	Y	Y	Y	Y	Y
Geographic Controls	N	Y	Y	Y	Y
Demographic Controls	N	N	Y	Y	Y
Conflict Controls	N	N	N	Y	Y
Modern Controls	N	N	N	N	Y
F	2	2	3	5	5
N	325	325	325	325	325

(b) The effect of Massacres on Homicide Rates(2016-2019)

	(1)	(2)	(3)	(4)	(5)
Massacre Dummy	5.991	-14.343	-24.036	-17.956	-15.519
	(45.980)	(6.327)**	(15.401)	(9.156)**	(10.282)
Average Precipitation (1961-1981)	Y	Y	Y	Y	Y
Geographic Controls	N	Y	Y	Y	Y
Demographic Controls	N	N	Y	Y	Y
Conflict Controls	N	N	N	Y	Y
Modern Controls	N	N	N	N	Y
N	325	325	325	325	325

Notes: All regressions include average precipitation from 1961 to 1981. Geographic controls include ruggedness and elevation. Demographic controls are the share of indigenous in 1981, share literate in 1981 and a minority language dummy. Conflict controls are base presence and confrontations rate. Finally, modern controls include: urban population share, share aged 15-19, share male, share of imigrants and share of imigrants from massacred municipalities. Conley standard errors in parenthesis, error correlation allowed up to 2.5 degrees difference in latitude and longitude (approximately 278km at Guatemala's latitude).

*p<0.10, ** p<0.05, *** p<0.01

6 Violence and Trust

The literature on the effects of civil-war violence in local cooperation (e.g Bauer et al. 2016) has found that the first tends to increase the latter. At the same time, the literature on gangs suggests that they are responsible for a large share of homicides in Guatemala and that more local cooperation and social capital could impact their recruitment. Moreover, increased social capital could allow for more predictable and peaceful resolution of conflicts

In this section, I use generalized trust as a proxy for local cooperation/social capital and investigate its explanatory power for the reductive effects of massacres on crime. The hypotheses are that: (1) the massacre-induced trauma increased local cooperation, (2) local cooperation reduces homicide rates.

Since massacres can affect homicide rates in a variety of ways, a valid instrument for massacres (e.g. precipitation) is not necessarily a good instrument for any of its mechanisms. Therefore, I rely on the studying correlations of (current) trust with homicides and massacres in order to verify if these are consistent with the last paragraph's story. If generalized trust[24] reflects different levels of local cooperation, a negative correlation between massacres and trust would be at odds with hypothesis (1).[25] Likewise, a negative correlation between trust and homicide rates is arguably more likely if hypothesis (2) is true.[26]

Tables 13 and 14 show the correlation between massacres and generalized trust. Without any control variables, the OLS regression coefficient is 0.15 and statistically significant. If interpreted as causal, this coefficient would imply that a change from zero to 25.5 in the massacre rate would lead to an increase of 3.4 in the share of people with high trust. Controlling by geographic, demographic (conflict time), or conflict variables do not change this result meaningfully.

As a further check of the quality of the data, I also estimate OLS regressions with Trust in the Military as the dependent variable. Unsurprisingly, the municipalities who suffered more massacres also have lower trust in the Military (tables 15 and 16).

The correlation between generalized trust and homicide rates is negative. The OLS coefficients (tables 17 and 18) range between [-0.83, -0.03] and are significant in all but two cases. If interpreted causally, these would lead to the conclusion that an increase of one standard deviation in trust (13.5) would lead to something between a 0.4 and 11.2 decrease in homicide rates.

In the absence of a good instrument for the effects of massacres on trust, and of these on homicide rates, it is not possible to identify how much of the main effect (of massacres on homicide rates), comes from trust itself. Nevertheless, the correlations found in this section are consistent with trust being one of the

[24]Generalized trust is obtained by asking the local population whether they think that "most people can be trusted". Data is from the 2000-2017 period, more details in the appendix.

[25]It would not refute hypothesis (1), but defending it would demand affirming that other factors are driving this correlation.

[26]A Bayesian update could theoretically be done with a negative correlation, increasing the posterior probability of hypothesis (2). Apart from the direction of the update, finding a posterior probability would require a prior and very strong assumptions. I avoid those in this paper.

Table 13: Generalized Trust and Massacres: OLS regressions

	Generalized Trust	Generalized Trust	Generalized Trust	Generalized Trust
Massacre Rate	0.15	0.15	0.14	0.13
	(0.03)***	(0.03)***	(0.03)***	(0.03)***
Military Base	N	Y	N	N
Ruggedness	N	N	Y	N
Elevation	N	N	N	Y
N	229	229	229	229

Notes: Conley standard errors in parenthesis, error correlation allowed up to 2.5 degrees difference in latitude and longitude (approximately 278km at Guatemala's latitude).

*p<0.10, ** p<0.05, *** p<0.01

mechanisms explaining the counterintuitive effects of past violence in today's violence.

Table 14: Generalized Trust and Massacres: OLS regressions

	Generalized Trust	Generalized Trust	Generalized Trust	Generalized Trust
Massacre Rate	0.09	0.12	0.14	0.13
	(0.03)***	(0.02)***	(0.03)***	(0.03)***
Share Indigenous (1981)	Y	N	N	N
Literacy (1981)	N	Y	N	N
Confrontations Rate (1981)	N	N	Y	N
Minority Language (1981)	N	N	N	Y
N	229	229	229	229

Notes: Conley standard errors in parenthesis, error correlation allowed up to 2.5 degrees difference in latitude and longitude (approximately 278km at Guatemala's latitude).

*p<0.10, ** p<0.05, *** p<0.01

Table 15: Trust in the Military and Massacres: OLS regressions

	Trust in the Military	Trust in the Military	Trust in the Military	Trust in the Military
Massacre Rate	-0.10	-0.10	-0.09	-0.10
	(0.03)***	(0.03)***	(0.02)***	(0.02)***
Military Base	N	Y	N	N
Ruggedness	N	N	Y	N
Elevation	N	N	N	Y
N	223	223	223	223

Notes: Conley standard errors in parenthesis, error correlation allowed up to 2.5 degrees difference in latitude and longitude (approximately 278km at Guatemala's latitude).

*p<0.10, ** p<0.05, *** p<0.01

Table 16: Trust in the Military and Massacres: OLS regressions

	Trust in the Military	Trust in the Military	Trust in the Military	Trust in the Military
Massacre Rate	-0.07	-0.06	-0.09	-0.10
	(0.02)***	(0.02)**	(0.03)***	(0.03)***
Share Indigenous (1981)	Y	N	N	N
Literacy (1981)	N	Y	N	N
Confrontations Rate (1981)	N	N	Y	N
Minority Language (1981)	N	N	N	Y
N	223	223	223	223

Notes: Conley standard errors in parenthesis, error correlation allowed up to 2.5 degrees difference in latitude and longitude (approximately 278km at Guatemala's latitude).

*p<0.10, ** p<0.05, *** p<0.01

Table 17: Generalized Trust and Homicide Rates: OLS regressions

	Homicide Rate	Homicide Rate	Homicide Rate	Homicide Rate
Generalized Trust	-0.21	-0.18	-0.15	-0.03
	(0.06)***	(0.06)***	(0.04)***	(0.04)
Military Base	N	Y	N	N
Ruggedness	N	N	Y	N
Elevation	N	N	N	Y
N	229	229	229	229

Notes: Conley standard errors in parenthesis, error correlation allowed up to 2.5 degrees difference in latitude and longitude (approximately 278km at Guatemala's latitude).

*p<0.10, ** p<0.05, *** p<0.01

Table 18: Generalized Trust and Homicide Rates: OLS regressions

	Homicide Rate	Homicide Rate	Homicide Rate	Homicide Rate
Generalized Trust	-0.01	-0.13	-0.19	-0.12
	(0.04)	(0.06)**	(0.07)***	(0.05)***
Share Indigenous (1981)	Y	N	N	N
Literacy (1981)	N	Y	N	N
Confrontations Rate (1981)	N	N	Y	N
Minority Language (1981)	N	N	N	Y
N	229	229	229	229

Notes: Conley standard errors in parenthesis, error correlation allowed up to 2.5 degrees difference in latitude and longitude (approximately 278km at Guatemala's latitude).

*p<0.10, ** p<0.05, *** p<0.01

7 Conclusion

In this paper, I estimate the effects of massacres on homicides 37 years later. The results point to a negative effect, with an estimated reduction in 17 homicides per 100,000 population by moving from zero massacres to the affected municipality average. The change is equivalent to more than three times the current US homicide rate. This result is robust to different measures of massacre intensity, homicide rates and demographic controls.

Affected areas report more trust than non-affected areas. Although this paper does do not aim to estimate how much of the homicide rates decrease can be attributed to trust-related variables, this paper's evidence and the literature on social effects of civil-war (e.g Bauer et al. (2016)) suggests it is part of the story.

The findings presented in this paper are of significance from both a historical and policy perspective. From the historical side, it helps to understand the consequences of traumatic events and the origins of Guatemala's current violence problem. The negative effects of past violence point to an important and understudied role of local cooperation in the determination of crime levels. Policymakers may look for peaceful ways to improve social capital.

References

Ball, Patrick (1999). *AAAS/CIIDH database of human rights violations in Guatemala (ATV20.1)*. URL: http://hrdata.aaas.org/ciidh/data.html%20(7/19/2020)..

Ball, Patrick, Paul Kobrak, and Herbert F. Spirer (1999). *State Violence in Guatemala, 1960-1996: A Quantitative Reflection*. American Association for the Advancement of Science.

Bateson, Regina (2017). "The socialization of civilians and militia members". In: *Journal of Peace Research*.

Bauer, Michal, Christopher Blattman, Julie Chytilová, Joseph Henrich, Edward Miguel, and Tamar Mitts (2016). "Can War Foster Cooperation?" In: *Jornal of Economic Perspectives*.

Bellows, John and Edward Miguel (2009). "War and local collective action in Sierra Leone". In: *Journal of Public Economics*.

Brands, Hal (2010). "Crime, Irregular Warfare, and Institutional Failure in Latin America: Guatemala as a Case Study". In.

CEH, (Commission for Historical Clarification) (1999). *Guatemala Memoria del Silencio*.

Cesur, Resul and Joseph J. Sabia (2016). "When War Comes Home: The Effect of Combat Service on Domestic Violence". In: *The Review of Economics and Statistics*.

Chamarbagwalaa, Rubiana and Hilcías E Morán (2011). "The human capital consequences of civil war: Evidence from Guatemala". In: *Journal of Development Economics*.

Crisis Group (2014). *Corridor of Violence: The Guatemala-Honduras Border*. 52.

Cruz, Jose Miguel, Manolya Tanyu, Yulia Vorobyeva, Yemile Mizrahi, Andi Coombes, Josué Sánchez, Chandler Hill, and Patricia Campie (2020). *A Study of Gang Disengagement in Guatemala*. USAID.

Dudley, Steven (2016). *Homicides in Guatemala: The challenge and lessons of disaggregating gang-related and drug trafficking-related murders.* Democracy International.

Earth Resources Observation and Science Center (1997). *USGS 30 ARC-second Global Elevation Data, GTOPO30. Research Data Archive at the National Center for Atmospheric Research, Computational and Information Systems Laboratory.*

Evans, Michael and Jesse Franzblau (2013). *Mexico's San Fernando Massacres: A Declassified History*. Book no. 445.

Fick, Stephen E. and Robert J. Hijmans (2017). "WorldClim 2: new 1-km spatial resolution climate surfaces for global land areas". In: *International Journal Of Climatology*.

Funk, C.C., P.J Peterson, M.F Landsfeld, D.H. Pedreros, J.P. Verdin, J.D. Rowland, B.E. Romero, G.J. Husak, J.C. Michaelsen, and A.P. Verdin (2014). "A Quasi-Global Precipitation Time Series for Drought Monitoring". In: *U.S. Geological Survey Data Series 832*. URL: http://iridl.ldeo.columbia.

edu/SOURCES/.UCSB/.CHIRPS/.v2p0/.daily-improved/.global/.0p25/X/-92/-88/RANGE/Y/14/18/RANGE/prcp/datafiles.html.

Galiani, Sebastian, Martín A. Rossi, and Ernesto Schargrodsky (2011). "Conscription and Crime: Evidence from the Argentine Draft Lottery". In: *American Economic Journal: Applied Economics*.

Guberek, Tamy and Margaret Hedstrom (2017). "On or off the record? Detecting patterns of silence about death in Guatemala's National Police Archive". In: *Archival Science*.

Harris, I., P.D. Jones, T.J. Osborn, and D.H. Lister (2013). "Updated high-resolution grids of monthly climatic observations – the CRU TS3.10 Dataset". In: *International Journal Of Climatology*.

IPUMS (2019). *Integrated Public Use Microdata Series, International: Version 7.2 [dataset]*.

Maarten J. Voors, Eleonora E. M. Nillesen, Philip Verwimp, Erwin H. Bulte, Robert Lensink, and Daan P. Van Soest (2012). "Violent Conflict and Behavior: A Field Experiment in Burundi". In: *American Economic Review*.

Mathieu Couttenier, Veronica Petrencu, Dominic Rohner, and Mathias Thoenig (2019). "The Violent Legacy of Conflict: Evidence on Asylum Seekers, Crime, and Public Policy in Switzerland". In: *American Economic Review*.

Mattina, Giulia La (2017). "Civil conflict, domestic violence and intra-household bargaining in post-genocide Rwanda". In: *Journal of Development Economics*.

Memoria Histórica, (REMHI) Recuperación de la (1998). *Guatemala: Nunca más*. Guatemala: Oficina de Derechos Humanos del Arzobispado.

Mezquita, Rocio (2000). "The Guatemalan Commission for Historical Clarification". In: *Clarification. In Making the Case: Investigating Large Scale Human Rights Violations Using Information*. Patrick Ball, Herbert Spirer and Louise Spirer. Washington, DC: AAAS.

Miguel, Edward, Sebastian M Saeigh, and Shanker Satyanah (2011). "Civil War Exposure and Violence". In: *Economics & Politics*.

Moya, Andres (2018). "Violence, psychological trauma, and risk attitudes: Evidence from victims of violence in Colombia". In: *Journal of Development Economics*.

Nunn, Nathan and Diego Puga (2012). "Ruggedness: The Blessing of Bad Geography In Africa". In: *Review of Economics and Statistics*.

Raisa Sara (2020). *Civil Conflict and Later Life Crime*. Department of Economics, Texas A&M University.

Schwartz, Rachel A and Scott Straus (2018). "What drives violence against civilians in civil war? Evidence from Guatemala's conflict archives". In: *Journal of Peace Research*.

Sharp, Lynsey Nicole (2017). "From Guatemaltecas to Guerrilleras: Women's Participation in the Ejército Guerrillero de los Pobres". Master Thesis, Latin American Studies. Nashville, Tennessee: Vanderbilt University. URL: https://ir.vanderbilt.edu/bitstream/handle/1803/11260/Sharp.pdf?sequence=1&isAllowed=y.

Sullivan, Christopher M (2015). "Undermining Resistance: Mobilization, Repression, and the Enforcement of Political Order". In: *Journal of Conflict Resolution*.

— (2016). "Political Repression and the Destruction of Dissident Organizations: Evidence from the Archives of the Guatemalan National Police". In: *World Politics*.

United Nations Office on Drugs and Crime (2007). *Crime and Development in Central America*.

— (2019). *GLOBAL STUDY ON HOMICIDE Homicide: extent, patterns, trends and criminal justice response*.

— (2020). *DATAUNODC*. URL: https://dataunodc.un.org/ (visited on 07/17/2020).

Winton, Alisa (2006). "Youth, gangs and violence: Analysing the social and spatial mobility of young people in Guatemala City". In: *Children's Geography*.

A Data construction

Precipitation

Data on precipitation comes from World Clim. [27] Monthly precipitation from 1961 to 2018 is measured with a 2.5 minutes spatial resolution grid. In other words, the raw data consist of a temporal series of rectangular pixels with sides of about 4.5 km (in Guatemala's Latitude).

To convert this data from the pixel level to the municipality level, I take a weighted average of pixels whose areas intersect those of the municipalities. The weights correspond to the share each pixel has of the municipality area. [28]

For the regression analysis, I compute the variable **Precipitation (1982)**, which is the sum of monthly municipal precipitation at the height of conflict, 1982. Similarly, **Precipitation (1961-1981)** measures the mean of this annual sum, between 1961 and 1981 and serves as a control for characteristics correlated with the historical level of rain.

Homicides

I use police data (Policia Nacional Civil) as a source for homicides.[29] **Homicide rates** are constructed by dividing the number of victims by the 2018 population, and multiplying the result by 100,000. As some municipalities are very small and do not register murders all years, I use the average between 2016-2019 homicide rates for most estimations. Figure 4 shows the spatial distribution of this variable in the sample

EGP Presence

The data on Ejército Guerrillero de los Pobres(EGP) presence is from Sharp (2017) .

Other Conflict Variables

Conflict data were obtained in the replication files of Sullivan (2016). Studying the repression of dissident organizations, the author compiled ample data regarding the Guatemalan conflict between 1975-1985, like monthly municipal level counts of massacres and challenges to the government. It also includes a dummy for presence of military and police bases.

For massacres, the author coded events described in CEH (1999). The CEH defined massacres as "the execution of five or more people, in the same place, as part of the same operation and whose victims were in an indefensible

[27] Harris et al. (2013) and Fick and Hijmans (2017)

[28] More formally: $P_{it} = \sum_{j=1}^{J} \frac{A_{ij}}{A_i} P_{jt}$. Where A_{ij} is the size of the area of municipality i covered by pixel j and P_{jt} is the precipitation in pixel j, time t. P_{it} is the corresponding municipality level precipitation.

[29] The data from for 2016-2019 is available in the Guatemala National Statistics Institute (INE) website. The dataset reports all the known victims, with date and municipality of the murder, besides other information.

state."(Mezquita, Rocio 2000). I aggregated these counts across 1982, divided them by the 1981 municipal population and multiplied by 100,000 in order to create comparable rates per 100,000 population. The resulting number is the **Massacre Rate**.

confrontations were coded by Sullivan (2016) from police documents. confrontations [30] include violent and peaceful disputes and "are operationalized as public efforts by organized challengers to press claims against political authority. Examples include strikes, demonstrations, marches, roadblocks, targeted killings, arson, kidnapping, and the taking of hostages." (Sullivan 2016). I create the variable **confrontations Rate** by aggregating the municipal count in the year before the height of the conflict (1981), dividing it by the 1981 population and multiplying the result by 100,000.

Terrain

Data on elevation is from Earth Resources Observation and Science Center (1997), available at `http://www.webgis.com/terr_world.html` and consists of a 30 arc seconds (approximately 1 kilometer) grid. From there, I calculate ruggedness at the pixel level,[31] as well as the municipal elevation and terrain ruggedness (following Nunn and Puga 2012) using the same weighted average standard of the precipitation variables.

Demographic Variables

Demographic data includes municipal population (in 1973, 1981 and 2018), share indigenous (1973 and 1981), share literate (1973 and 1981) and share of urban, male and young population (2018). The data is originally from the Guatemalan Census of the corresponding years.

The 2018 microdata was directly downloaded from the census' website, while the older numbers were obtained in the replication files of Sullivan (2016).

Language

Linguistic communities are mapped in CEH (1999) . I spatially matched the CEH (1999) data with 1973 municipalities boundaries to get municipal level data. The variable **Minority Language** is a dummy equal to one when the municipality is in a non-Spanish linguistic community.

Trust Variables

The variables generalized trust and trust in the military were constructed using data from the Latinobarometro. Latinobarometro asks interviewees whether "most people can be trusted". I compute generalized trust as the percent of individuals who answer positively to this question, among those who answer.

[30] Originally named "Overt, collective challenges".
[31] Following Nunn and Puga (2012).

Latinobarometro also prompt respondents to use a four-step scale to measure their trust in the military.[32] I compute trust in the military as the percent of individuals with a who gave one of the top two possible answers.

Latinobarometro does not interview people from all municipalities every year. I use data from all the years with a survey (most years between 2000-2017) to construct municipal level data measures of trust. Nevertheless, 30% of the municipalities are still absent of the sample.

Migration

Migration data constructed from the 2018 Guatemalan census. The share of migrants of a municipality correspond to the ratio between the number of individuals born there who live at another municipality and the number of individuals who were born there. For this ratio, I only consider persons who were born up to 1982.

Municipal Boundaries

The variables described here collected in different points of time, using different geographical units. Data from Sullivan (2016) has 1973 municipal boundaries as unit, while homicides were first constructed with the 2018 boundaries. Between 1973 and 2018, some municipalities split (most of them after democratization) and the number of them went from 325 to 340. I use census maps (ceded by IPUMS 2019) to conform 2018 data to the 1973 boundaries,[33] and run all regressions at that level.

[32] A lot of trust, some trust, little trust, no trust.

[33] So, if one municipality A split into B and C, municipality A homicides in 2018 will correspond to the sum of homicides in B and C.