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The legacy of Mexico's Drug War on youth political attitudes

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Abstract: We investigate the impact of childhood exposure to organized criminal violence on sociopolitical attitudes in Mexico, where an entire generation of youths has been raised amid the country's most violent conflict over the past century. We fielded an in-person survey to nearly 3,000 urban youths, measuring various sociopolitical attitudes such as trust in institutions, interpersonal trust, and vote choice. To assess the impact of violence exposure on these attitudes, we construct measures of childhood exposure for each individual by matching them with historical trends in homicide rates and military confrontations from the municipality where they grew up. Our findings indicate that exposure to both types of violence during the first ten years of life is associated with up to a 20 per cent decrease in reported interpersonal and political trust. We also find evidence of negative impacts on support for the political parties that ruled the country during that period. These results have significant implications for the consolidation of Mexico's young democracy. Understanding the long-term effects of exposure to violence during childhood is critical for designing effective policies to promote social and political stability, democratic norms, and social cohesion among the younger generation.

Key words: organized crime, sociopolitical attitudes, Mexico, violence, trust, democracy, social cohesion

JEL classification: K42

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Parts of the appendix are adapted from a full report the authors delivered to USAID and an additional working paper which utilizes the survey data used for this study.

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1 Introduction

Over the past decade and a half, an entire generation of Mexicans has been raised amid the most violent conflict in the country over the past century. Since the start of the 'Drug War' in December 2006, escalating criminal violence has affected various regions of Mexico, resulting in over 400,000 homicides and around 100,000 disappearances.[1] Millions of Mexicans have transitioned to adulthood witnessing sharp increases in levels of violence and an unprecedented process of militarization of public life. This generation now makes up a significant portion of the country's voting-age population. Despite such a profound transformation, our understanding of the sociopolitical impact of this conflict among the youth remains limited. This study aims to address two fundamental questions: How has the Drug War impacted the political beliefs and preferences of Mexico's youth? And what implications does this have for the consolidation of Mexico's democracy?

Previous research has examined various aspects of the causes and consequences of organized criminal violence in Latin America—particularly looking at the cases of Brazil, Colombia, and Mexico. However, there has been little research dedicated to understanding how exposure to violence and increased militarization shape political attitudes, identities, and beliefs among the youth. This is an important gap in the literature since youths account for an overwhelmingly high percentage of victims and perpetrators of criminal violence in Latin America and elsewhere (Chioda 2017; Muggah and Tobón 2018; Rivera 2016; Sweeten et al. 2013). The literature on the formation of political identities and beliefs suggests that the impacts of childhood exposure to violence can be profound. Several scholars have shown that childhood experiences and socialization processes heavily influence political attitudes, behaviour, and preferences in adult life (Campbell et al. 1980; Green et al. 2008; Healy and Malhotra 2013). Furthermore, there is a growing literature indicating that exposure to crime and violence causally affects political attitudes and behaviour (Adhvaryu and Fenske 2023; Balcells and Torrats-Espinosa 2018; Bateson 2012; Bauer et al. 2016; Hong and Kang 2017).

We investigate the causal effects of childhood exposure to criminal violence and military confrontations—within the context of Mexico's Drug War—on interpersonal and institutional trust. We use an original in-person survey of 2,880 individuals. This survey was conducted in June 2021 and is representative of Mexico's urban population aged 16–29. The core of our empirical strategy exploits variation in exposure to violence and military confrontations during childhood based on respondents' geographic location and date of birth. In other words, we test whether respondents exposed to varying levels of violence or military confrontations during childhood in their communities exhibit different levels of interpersonal and institutional trust. This empirical approach resembles the identification strategy used in previous studies that look at the impact of childhood exposure to violence on human capital accumulation and health-related outcomes (Justino et al. 2014; Le and Nguyen 2020; Leon 2012; Shemyakina 2011). Based on previous research, we expect childhood exposure to drug-related violence, both homicides and the government's militarized response, to negatively affect levels of interpersonal trust and trust in the government (particularly trust in institutions in charge of security).

We employ linear models with random intercepts both for respondent birth year and municipality to explore the effects of violence exposure on political and interpersonal trust. We measure exposure to violence using annual, municipal-level homicide data. We then measure militarization using data regarding confrontations between the military and organized crime, collected by Flores-Macías and Zarkin (2021). We examine the degree to which these factors influence trust in the police, government, and military, as well as trust in one's family and neighbours. Ultimately, we find that exposure to violence generally speaking (homicides) during the first ten years of one's life has an overall negative

[1] These figures are based on data from the National Institute of Statistics and Geography (INEGI) and the National Registry of Missing or Disappeared Persons (RNPDNO).

effect across the board on political and interpersonal trust. We then find that exposure to militarization during one's youth has the strongest and most consistent negative effect on trust in institutions that were involved in the Drug War—that is, the federal police, the federal and state governments, and the army. We also find negative impacts on interpersonal trust—family and neighbours.

Our study contributes to several strands of literature. First, it adds to scholarly work showing that childhood experiences heavily influence the formation of political identities (Campbell et al. 1980; Jennings and Niemi 2014). Second, numerous studies have demonstrated that violence during childhood impacts education (Justino et al. 2014; Leon 2012), health (Akresh et al. 2012), and other development outcomes. We show that political attitudes are also affected by exposure to violence during childhood. Finally, our study is closely related to research that examines how exposure to violence affects political attitudes and behaviour (Balcells and Torrats-Espinosa 2018; Blattman 2009; Gilligan et al. 2014; Voors et al. 2012). This literature has ignored the long-term impact of violence exposure during childhood and formative years.

2 Theoretical framework

2.1 Childhood experiences and the formation of political beliefs

Several scholars have shown that childhood experiences heavily influence the formation of political attitudes and behaviour, as well as policy preferences. In particular, the adoption of political identities during childhood seems to be a strong predictor of political attitudes and behaviour in adult life (Campbell et al. 1980; Green et al. 2008; Healy and Malhotra 2013). This literature has primarily focused on understanding the development of political identities in the context of the United States and Western Europe. Some of the most influential work has been conducted by M. Kent Jennings and Richard Niemi, who pioneered a series of longitudinal, inter-generational studies of political attitudes among American youth. Their research has consistently shown a strong and persistent relationship between processes of childhood socialization and political beliefs.

Existing work on how childhood experiences influence the formation of political beliefs has largely ignored how exposure to violence during childhood or formative years influences people's political attitudes and behaviour. Notably, Lupu and Peisakhin (2017) find significant inter-generational effects of violence on ethnic identity and political attitudes among Crimean Tatars who suffered the violence of deportation. Hong and Kang (2017) show that South Koreans who experienced violence in their childhood are less supportive of the government, especially the administration and the military.

If exposure to crime and violence during childhood is capable of reshaping political views, attitudes, and behaviours, it is of theoretical and empirical import to understand how and to what extent, particularly in contexts with high levels of violence and impunity.

2.2 Exposure to violence and political behaviour

A growing body of micro-empirical research on the effects of violent conflict on political behaviour shows that exposure to violence increases social cohesion and political engagement. Using experimental or quasi-experimental approaches, many of these studies have found that individuals exposed to wartime violence exhibit higher civic and political engagement levels after the conflict. For example, Bellows and Miguel (2009) found that conflict-related displacement and deaths in Sierra Leone led to greater political participation and political awareness. Similarly, Blattman (2009) presents evidence for a connection linking past violence in Northern Uganda to increased engagement in politics among randomly abducted ex-combatants. These studies measure exposure to violence at the individual level,

but similar effects of wartime violence have been observed using indirect or community-level measures of conflict victimization (Balcells and Torrats-Espinosa 2018; Gilligan et al. 2014; Voors et al. 2012). Within the context of criminal violence, the evidence points in a similar direction: for instance, Bateson (2012) documents the existence of a strong link between crime victimization and political engagement. A recent meta-analysis suggests that the effects of wartime violence on social cohesion and political participation are persistent and fairly consistent across cases (Bauer et al. 2016).

However, some research has brought these relationships into question in recent years. Scholars suggest the effects of violence on important societal factors may affect individuals uniquely based on a variety of circumstances, including one's personal identity and community context (Brooks 2014; Laterzo 2021a; Ley 2018; Trelles and Carreras 2012). A more nuanced explanation of the effects of violence on political attitudes and behaviour is also documented in recent empirical studies that attempt to isolate the effects of specific types of violence. For example, Grossman et al. (2013) look at the effects of exposure to violence on political attitudes and behaviour by distinguishing between attitudes and behaviour towards in-group and out-group members. The authors find that exposure to combat among Israeli ex-combatants hardens attitudes towards the rival and reduces support for negotiation and compromise.

Several studies have documented that exposure to crime and insecurity has a detrimental effect on political trust, particularly in the case of Latin America, where organized criminal violence has become a major security threat. Exposure to crime, whether through personal victimization or residency in an insecure community, affects trust in a complex fashion. Crime can weaken social and institutional fabrics by increasing fear, suspicion, and distrust, both generally speaking and towards specific actors. Crime victimization has been shown to decrease social or horizontal trust (Corbacho et al. 2015; Salmi et al. 2007). In particular, Salmi et al. (2007) demonstrate that victimization and exposure to crime news can decrease social trust among adolescents. However, they do not examine if this effect is persistent as individuals age.

Furthermore, crime victimization and insecurity typically lead to decreased political trust towards specific, security-related institutions such as the local police and judicial system (Blanco 2013; Blanco and Ruiz 2013; Corbacho et al. 2015; Malone 2010). However, Malone (2010) argues that this effect on specific institutional trust is context-specific. In countries with lacklustre justice systems, personal experience with crime erodes support only for the police. Notably, public fear of crime and victimization does go beyond affecting specific institutions. In poor-performing, high-crime countries, fear of crime in one's neighbourhood has a negative relationship with measures of diffuse support. Researchers find that crime exposure can transcend measures of specific support and affect individuals' trust in major national institutions and the entire regime (Blanco and Ruiz 2013; Malone 2010).

Examining trust, and what might lead to its decrease, is of paramount importance. Cultural theories suggest that a civic culture with high levels of institutional trust and interpersonal trust is vital for democracy. Institutional trust encourages political involvement and contributes to support for democratic ideals, even in the contexts of hybrid regimes (Mishler and Rose 2001). Where we see low trust, we often see the rise of forms of government that can be quite detrimental to democracy—such as populism. When public trust in political institutions is low, voters are attracted to candidates that portray themselves as radical 'outsiders' (Doyle 2011; Seligson 2007). This is particularly relevant in the context of Mexico with the rise of President Andrés Manuel López Obrador, who is often considered to engage in populist behaviours and forms of leadership. Further, as mentioned by Mishler and Rose (2001), trust is key to political participation, a necessary portion of a functioning democracy. In Latin America, when trust in elections is low, citizens are less willing to participate. If citizens do not trust the institution of elections and believe that their vote will have no impact on results or policy outcomes, they will not engage.

In addition, trust dynamics can give rise to the erosion of other democratic principles and ultimately lead to repression by the state. Citizens exposed to criminal violence tend to report lower levels of satisfaction

with the way democracy works in their country (Fernandez and Kuenzi 2010). Pion-Berlin and Carreras (2017) examine how many Latin American citizens have low trust in the police, their capacity to fight crime effectively, and their respect for human rights. With regard to Mexico, there is evidence that criminal violence demobilizes voters (Ley 2018), and that support for the national incumbent party varies inversely with prevailing levels of violence (Ley 2017).

2.3 Empirical expectations

Building upon prior research and original fieldwork, youths' exposure to violence and militarization during the Drug War is expected to negatively affect both interpersonal and political trust—particularly with respect to institutions in charge of public security. Regarding political trust, exposure to higher homicide rates during childhood is likely to generate mistrust in the government (local, state, and federal), as well as in the police forces. The military forces (army and navy) have historically been among the highest-ranked institutions in terms of public opinion, but it is likely that those who grew up in areas with high incidences of violence and military confrontations regard these institutions in a less positive light.

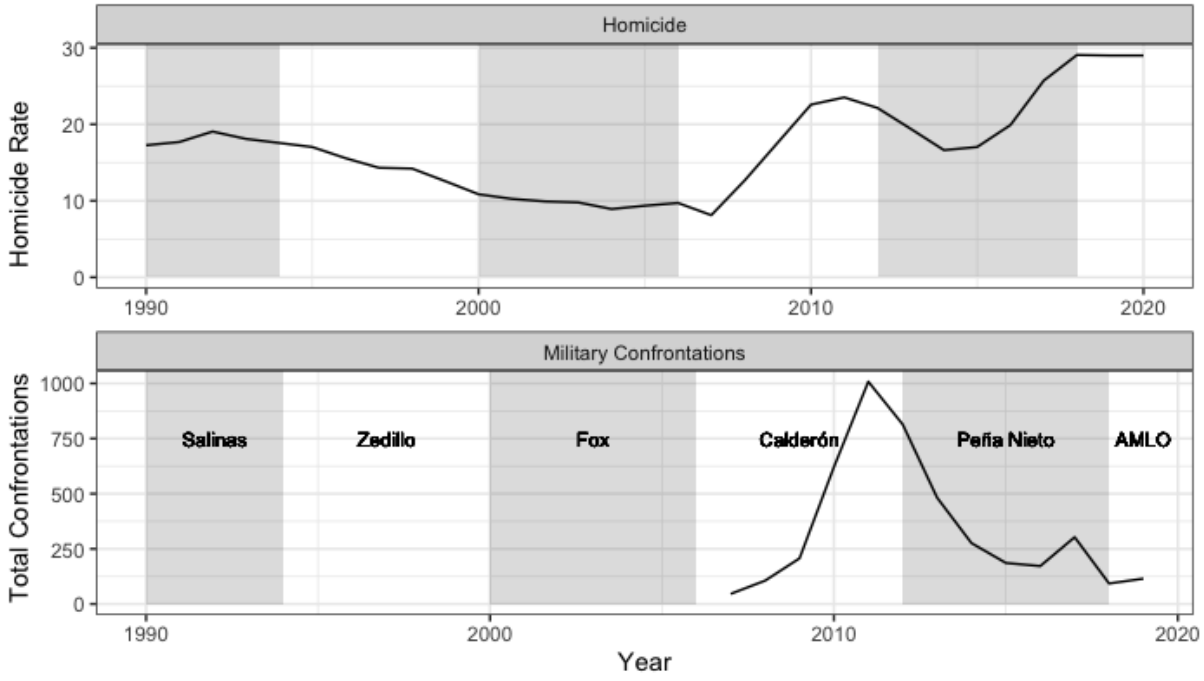
The deterioration of the social fabric in many communities as a result of drug-related violence suggests that youths' exposure to violence has had detrimental effects on patterns of interpersonal trust—that is, trust in the other members of their communities or neighbourhoods, and even trust in members of their own families.

3 A generation exposed to Mexico's Drug War

In December 2006, former Mexican president Felipe Calderón began a war against organized crime by deploying military forces throughout Northern and Western Mexico to fight against drug cartels. The beginning of his administration marked a significant policy shift in terms of public security. The Mexican army, which had not been trained to fight organized criminal groups, became the leading force behind 'Drug War' operations. Between 2012 and 2018, President Enrique Peña Nieto adopted a similar strategy towards organized crime. Although the number of military operations declined, the core of his public security strategy relied on capturing or killing criminal bosses, seizing drugs, and eradicating illicit crops. Despite applying a different rhetoric (he campaigned using a 'hugs, not bullets' approach to tackling organized crime), current president Andrés Manuel López Obrador has deepened the militarization of public security (Deare 2021).

The militarization of public security has failed to reduce crime and violence in Mexico. As shown in Figure 1 (upper panel), despite a modest decline in the homicide rate at the beginning of Peña Nieto's administration, homicides started trending upward again in 2015, and have remained at record high levels during López Obrador's administration. The production of violence involves a complex network of armed actors, including organized criminal groups, state security forces, and vigilante groups. Based on official data, nearly 400,000 people have been killed and around 90,000 have been reported as disappeared since the start of the Drug War. Although it is difficult to estimate how many homicides are directly related to the Drug War, there is growing evidence that the law enforcement approach adopted over the past 15 years—heavily focused on the beheading of criminal organizations and the militarization of public security—has contributed to the escalation of violence (Calderón et al. 2015; Dell 2015; Phillips 2015). Furthermore, recent research has found that the militarization of anti-drug efforts has decreased the state's capacity to provide public order and extract fiscal resources (Flores-Macías 2018).

Figure 1: Annual homicide rate and military confrontations across presidential administrations in Mexico (1990–2020)



Source: authors' compilation based on data from INEGI (upper panel) and the Secretariat of National Defense (lower panel).

The Drug War initiated by Felipe Calderón is a defining event in contemporary Mexican history. Of particular relevance is the fact that an entire generation of Mexicans was born, raised, and transitioned to adulthood during the most violent episode in the history of the country since the *Cristero* rebellion in the late 1920s. Those who were school-age children in the early years of the Drug War now comprise a substantial part of the voting-age population. Many of these young adults grew up in communities with unprecedentedly high levels of crime and violence, witnessing both the consolidation of the militarization of public security and the government's failures to make their communities safer. As shown in the bottom panel of Figure 1, Mexico experienced a sharp increase in the number of military confrontations between 2007 and 2012. This illustrates the drastic change in the security strategy under Calderón's administration.

It is also important to emphasize that youth account for an overwhelmingly high percentage of victims of criminal violence in Mexico. Based on official statistics from INEGI, the homicide rate among youths aged 15–24 increased three-fold between 2007 and 2011. As of 2020, 21 per cent of the victims of intentional homicide were 24 years old or younger, and more than half were under 34 years old. As a result of this, life expectancy among young males significantly declined in every state in the country (González-Pérez and Vega-López 2019).

4 Empirical approach

4.1 Data

Our goal is to explore the effects of violence and militarization during childhood on individuals' trust in a variety of actors. To examine these relationships, we rely on three main data sources: an original survey fielded in Mexico among young adults, official records of municipal homicides across the past few decades, and data regarding militarization. We will describe each of these data sources in turn in this section.

To measure the sociopolitical attitudes in question, we fielded an in-person survey of 2,880 young adults aged 16–29 in June 2021 across urban Mexico. Within the survey we asked a series of questions to isolate trust in the community and in political institutions. We asked respondents to rate their trust on a 1–7 scale, where 1 represents no trust at all and 7 represents a lot of trust. Respondents completed this exercise for the following groups: neighbours and family, the police (municipal, state, federal), the military (army and navy), and the government (federal, state, local).

Our survey was fielded in a face-to-face format by Buendía & Laredo, a leading survey firm based in Mexico. The sample is representative of urban Mexico for our age group of interest. In addition to ensuring our sample was representative of common sociodemographic characteristics, such as income and education level, we also employed a unique strategy to ensure it is representative of the various levels of municipal violence across the country (García-Ponce et al. 2023; Laterzo 2021b). Within this strategy we particularly considered three variables that capture variations in violence at this geographic level: homicide rates, reported non-homicide crime, and perceived levels of violence.

Although homicide rates are often used as a benchmark for the prevalence of violence, we chose to involve additional measures as homicide does not capture the complete reality of citizen insecurity. Because of this, we chose to examine non-homicide violence and perceived insecurity as well. These measures, however, are typically not available at the subnational level, particularly at units as small as the municipality.

To circumvent this issue, we rely upon measures available at the national and city levels from Mexico's National Survey of Urban Public Security (ENSU) and use multilevel regression and poststratification (MRP) to generate subnational measures (Gelman and Little 1997). MRP is a method of small-area estimation that allows for the generation of survey variable estimates at units below the survey's level of representativity. We model respondents' perceptions of violence and reported victimization as a function of selected sociodemographic characteristics (i.e. location, age, gender, occupation, education) and generate municipal-level estimates with such models via poststratification using Mexico's 2015 intercensus. We thus create 157 municipal estimates of both reported victimization and perceived insecurity. We then utilize these estimates and the most recently reported homicide rates collected by the Executive Secretariat of the National System of Public Security (SESNP) to stratify our survey sample. We limit our sampling frame to only include municipalities surveyed by ENSU, and order these units based on the three levels of insecurity via seriation. Using this method we generate a sample that is not only representative of urban Mexico for our age group of interest, but also of reported insecurity, reported victimization, and homicide rates at the municipal level.

Within our survey we ask respondents where they were born (either the municipality where they currently reside, or elsewhere). This is uncommon in current public opinion surveys in the area and allows us to measure exposure to violence and militarization in one's hometown during childhood. To do so, we rely upon two data sources. To capture exposure to violence we use municipal homicide rates reported by INEGI to create measures of homicide exposure during respondents' childhood.[2] To do so, we calculate the average homicide rate for each respondent for the first ten years of their lives based on their birth year and the homicide rate where they spent the majority of their childhood.[3] This measure provides us with a sense of general violence exposure during these periods of childhood.

[2] We rely upon two sources of homicide data in this study due to issues of data availability. INEGI provides the most reliable historical data on homicides, but SESNP provided the most reliable municipal homicide data for 2020 at the time of the fielding of our survey.

[3] For this current iteration of our analysis we only focus on individuals who currently live in the municipalities where they spent their childhood (about 84 per cent of our survey sample). For future iterations we will match the other 16 per cent of our sample with the municipality or state of their childhood.

Second, to capture exposure to militarization we utilize municipal-level data from the Secretariat of National Defense on the military's confrontations with criminal organizations between 2007 and 2018, originally collected by Flores-Macías and Zarkin (2021). The authors use this as a measure of military presence at the municipal level. We extend this assumption and use this measure as general militarization during the Drug War, both of the military and police. During the Drug War presidents often deployed the military along with both federal and state police to confront drug traffickers (Felbab-Brown 2014).

4.2 Identification strategy

We test whether survey respondents exposed to shocks of homicidal violence and militarization during their childhood exhibit significantly different levels of political and interpersonal trust. We use two different identification strategies based on each independent variable of interest.

First, we explore the effect of exposure to homicidal violence on trust. Our main independent variable of interest is the average exposure to homicides of each individual (based on their birth year and the municipality of residence). We examine if survey respondents exposed to higher levels of violence during their first ten years of life express different levels of trust relative to those who were born in a different year in the same municipality and those who were born in a different municipality but belong to the same cohort. Similar empirical strategies have been used in other studies addressing the impact of civil war on human capital accumulation and health-related outcomes (Chamarbagwala and Morán 2011; Leon 2012; Shemyakina 2011). We run different models with each of our ten dependent variables of interest, one for each government or community actor. We specify our model as a linear model with non-nested random intercepts for both year and municipality as follows:

$$y_i = \beta_1 V_i + \beta_2 X_i + \alpha_{j[i]} + \gamma_{k[i]} + \varepsilon_i \tag{1}$$

$$\alpha_j \sim N(0, \sigma_\alpha^2) \tag{2}$$

$$\gamma_k \sim N(0, \sigma_\gamma^2) \tag{3}$$

In this model, α and γ represent the non-nested random intercepts for the j municipalities and k birth years in our sample. Further, y_i is the outcome of interest (trust) and i is each individual respondent. X_i is a vector of individual-level control covariates. These are gender, socioeconomic status, and education level.[4] The parameter of interest is β_2, where V_i represents childhood exposure to violence, measured as an average of the homicide rate in the individual's municipality between their birth year and their tenth year of life. For example, the mean childhood exposure to violence during ages 0–10 for two respondents born in the same municipality in years t and $t+1$ is computed as the average homicide rate in years $(t,\ldots,t+10)$ and $(t+1,\ldots,t+11)$, respectively.

We use a similar modelling strategy to examine the role of militarization on respondent trust; however, we adapt the model slightly. We examine whether or not a respondent was older or younger than one of three age cutoffs (10, 12, and 15) in 2012 and interact this variable with exposure to militarization. We choose to dichotomize age based on the year 2012 as this year represents the end of the Felipe Calderón administration (the president who initiated the Drug War) and a turn towards significantly less militarization overall (see Figure 1). Therefore, those who were at the cutoff age or younger by 2012 would have experienced the majority of their formative years during the most repressive period of the Drug War. We explore three cutoff ages to determine if effects persist across different years of adolescence. We interact this dichotomous variable with the mean number of military confrontations during this initial period of the Drug War (2007–12). Following this logic, we model this relationship as follows:

$$y_i = \beta_1 M_i + \beta_2 D_i + \beta_3 M_i D_i + \beta_4 X_i + \alpha_{j[i]} + \gamma_{k[i]} + \varepsilon_i \tag{4}$$

[4] To create our socioeconomic status control variable, we rely upon a series of survey questions that determine respondents' possession of a series of assets. We then use principal component analysis (PCA) to create this variable.

$$\alpha_j \sim N(0, \sigma_\alpha^2) \tag{5}$$

$$\gamma_k \sim N(0, \sigma_\gamma^2) \tag{6}$$

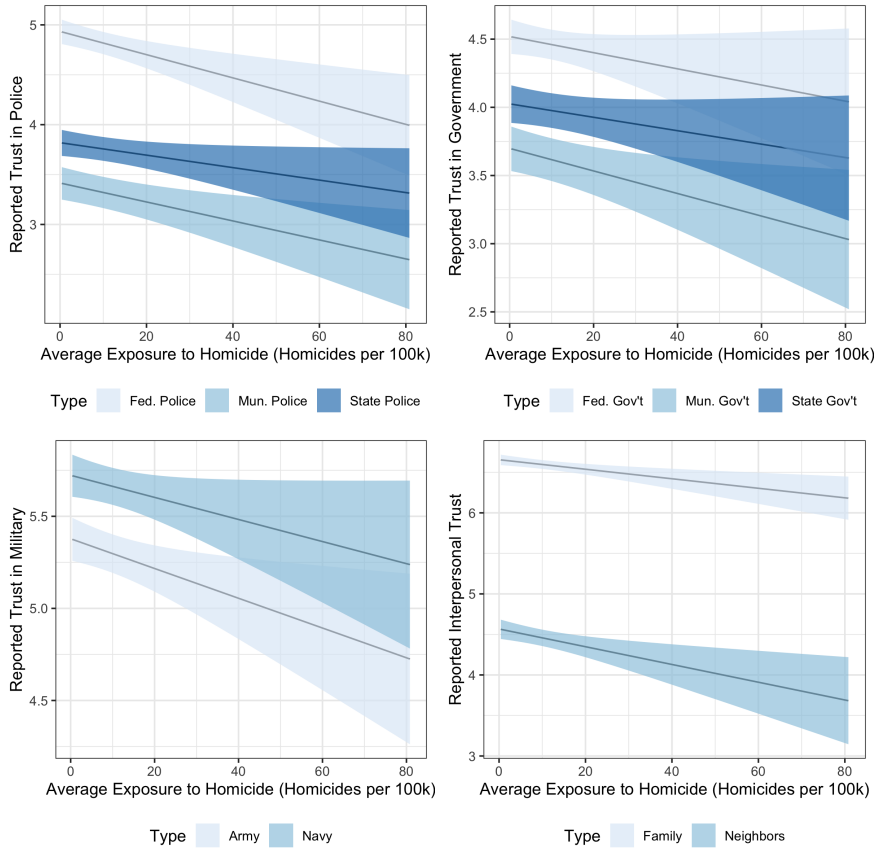
Once again, α and γ represent the non-nested random intercepts for the j municipalities and k birth years. y_i and i remain as our outcome of interest and each individual respondent, respectively. M_i represents the average number of military confrontations between 2007 and 2012 for each respondent, calculated based on both their age and municipality of residence. D_i is a dummy variable which is equal to 1 if the respondent was 10 years, 12 years, or 15 years or older in 2012, and 0 if not. Our estimand of interest is B_3, which captures the interaction effect between M_i and D_i and indicates whether or not there is a different effect of militarization based on a respondent's age group in 2012. Once again, X_i represents a vector of control covariates, which are the same as those used in our previous model.

5 Results

5.1 Exposure to homicides

In this section we present results from our models which explored the relationship between exposure to homicidal violence during one's youth and trust (political and interpersonal). Visualizations of predicted values from these models can be seen in Figure 2, and coefficients for all variables are provided in the Appendix. Overall, we find a consistent negative relationship between exposure to violence and trust, although the magnitude and significance of this relationship vary.

Figure 2: Predicted values of trust vs mean homicide exposure



Note: trust is reported on a 1–7 scale. Figures present predicted values from random-intercept models with 90 per cent semi-parametric bootstrapped confidence intervals.

Source: authors' compilation.

First, we find that exposure to homicidal violence is negatively associated with trust in all levels of the police. This effect is strongest when examining the federal police. As can be seen in Figure 2, a change in exposure to homicides from no exposure to the maximum level of exposure (80 per 100,000 on average during the first ten years of life) is associated with a drop in about one full point on the 1–7 trust scale (from about 5 to 4, or an approximately 20 per cent decrease in trust). Similar effects exist when examining trust in both state and municipal police, although the magnitude of the decrease in trust is smaller. All effects are significant, at minimum at the $p < 0.1$ level.

We also find a negative relationship between exposure to violence during childhood and trust in one's government. However, we find that this relationship is only significant when examining trust in the municipal government (at the $p < 0.05$ level). A change in exposure to homicides from 0 to the maximum value is associated with an 18 per cent decrease in trust in the municipal government (a change from about 3.7 to 3 on the 1–7 trust scale). We find a similar negative relationship between exposure and trust in the military; however, this relationship is only significant in the case of trust in the army ($p < 0.05$). An increase in exposure to violence from 0 to the maximum value is associated with an approximately 12 per cent drop in trust, from about 5.4 to 4.7 on the 1–7 trust scale.

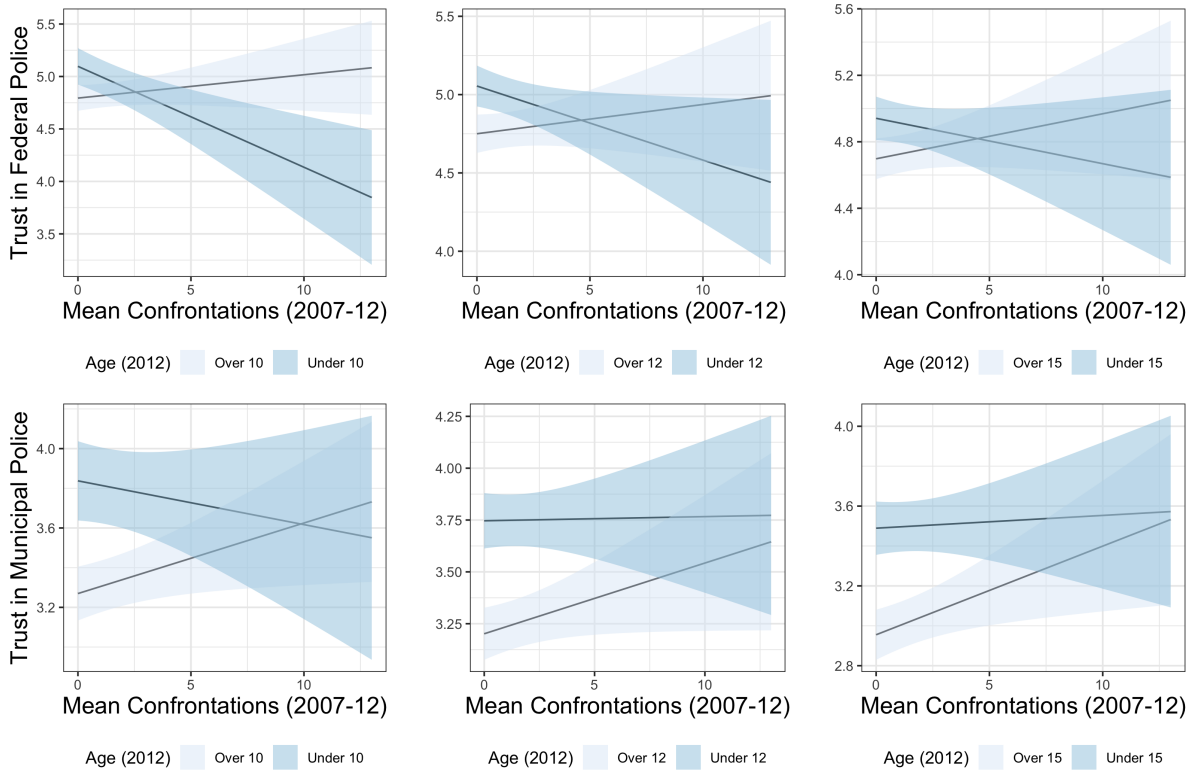
Finally, we find that exposure to homicide during one's youth is also associated with lower levels of interpersonal trust, both trust in one's family and one's neighbours. In particular, the drop in trust in neighbours is of a rather large magnitude—a 19 per cent drop when exposure increases from 0 to the maximum value. On the other hand, although trust in the family does decrease, the magnitude of this change is comparatively lower (about 7 per cent). Further, trust in the family is quite high comparatively speaking regardless of exposure to violence—the predicted value for trust in the family is always above 6 (on a 1–7 scale) across exposure levels.

5.2 Exposure to militarization

Here we present results regarding exposure to militarization during the height of the Drug War (2007–12) for different age groups on both political and interpersonal trust. We present visualizations of predicted values only for entities that we found experienced at minimum one statistically significant relationship with exposure. The full elaboration of results can be found in the Appendix.

We find that exposure to militarization negatively affects trust in the police for young individuals; however, this effect is only statistically significant for federal and municipal police. As can be seen in Figure 3, those under the ages of 10, 12, and 15 in 2012 exhibit decreased trust in federal police as exposure to militarization increases. Those over these age cutoffs experience an increase in trust. Interestingly, we find that this effect is strongest for those under ten years old. This indicates that exposure to militarization during one's most formative, youngest years has the most prominent effect. In particular, a change from no militarization to the maximum value of militarization leads to about a 25 per cent decrease in trust in the federal police among those under ten years old in 2012. We also find a statistically significant and negative interaction effect with respect to trust in the municipal police, but only when examining the ten-year cutoff. This relationship demonstrates that trust in municipal police actually increases among those over ten years old as militarization increases, but trust among younger individuals stays constant. We do not find a significant relationship when examining trust in the state police.

Figure 3: Predicted values of trust in federal police vs mean municipal military confrontations (2007–12) by age group



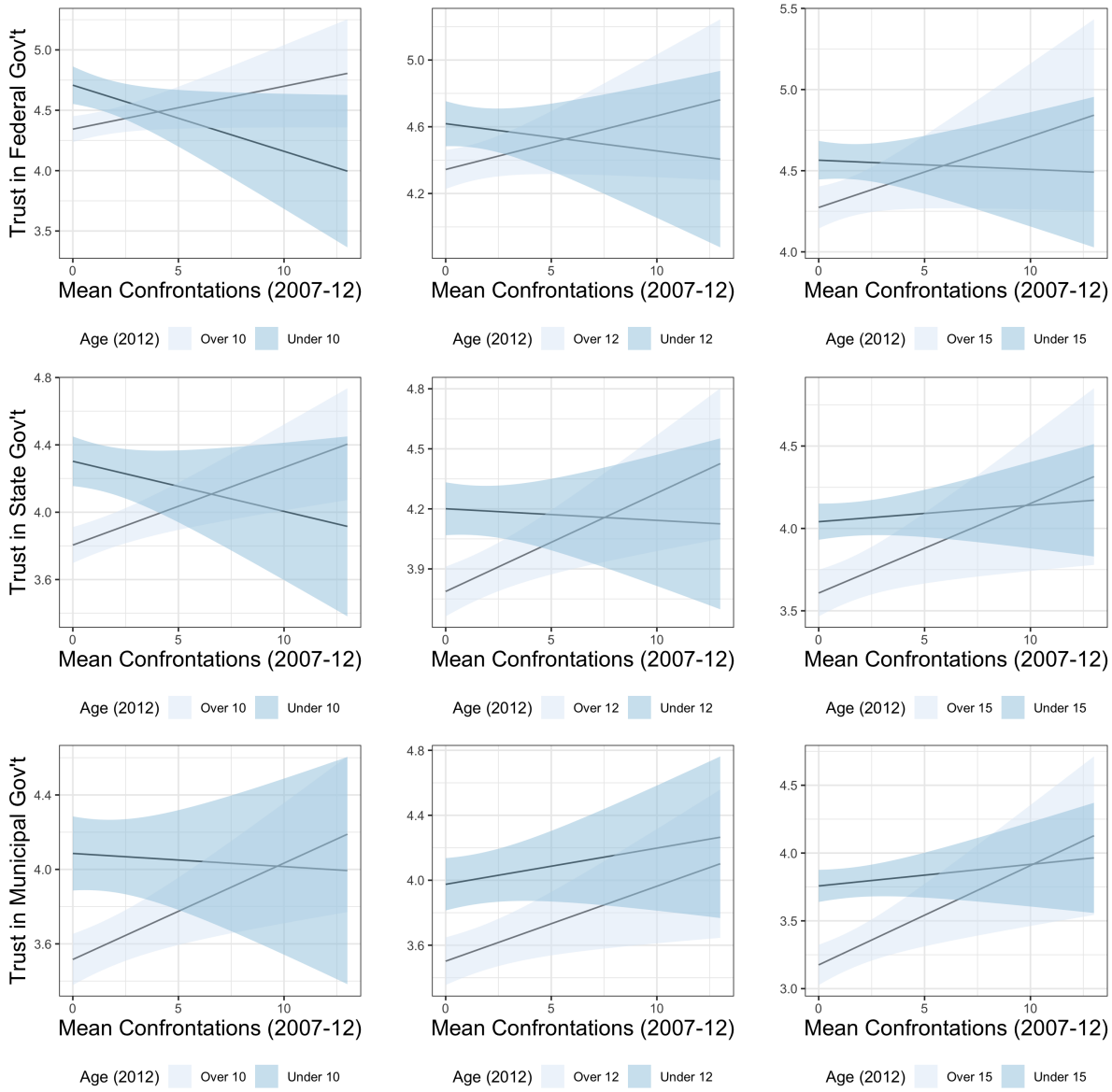
Note: trust is reported on a 1–7 scale. Mean confrontations are calculated as the average number of confrontations between the military and organized crime which each respondent was exposed to (based on their municipality of residence and birth year) for the years 2007–12. Figures present predicted values for each age group from random-intercept models with 90 per cent semi-parametric bootstrapped confidence intervals.

Source: authors' compilation.

In Figure 4 we present visualizations of the interaction between age and exposure and its effect on trust in different levels of government. With regard to trust in the federal government, we find that those under 10, 12, and 15 years old have lower levels of trust as exposure increases. However, this result is only significant when examining the ten-year cutoff. In this model, a change in exposure from zero to the maximum value results in a 15 per cent decrease in trust among those under ten years old. We find slightly different patterns when examining trust in state and municipal government. In the case of the state government, only models examining the cutoffs of 10 and 12 years are significant. These show a slight trend of decreased trust among those under the age cutoff and a rather prominent increase in trust among those above the age cutoff. In the case of municipal government trust, models examining the 10- and 15-year cutoffs are significant. They show that trust among those under the cutoffs stays rather consistent, while those above the cutoff similarly experienced increased trust with more militarization.

Figure 5 presents visualizations regarding trust in the military. Our models indicate that exposure to militarization under the age of 10, 12, or 15 is significantly associated with decreased levels of trust in the army. For example, we find that an increase in militarization from zero to the maximum value results in a 12 per cent drop in trust among those younger than ten years old. Conversely, the relationship is positive for those above ten years old in 2012. We find that the interaction between age and trust in the navy is only significant for the 10- and 15-year cutoff. Among those younger than ten, trust seems to decrease as militarization increases. Among those younger than 15 trust stays relatively constant, but increases among those older than 15.

Figure 4: Predicted values trust in government vs mean municipal military confrontations (2007–12) by age group

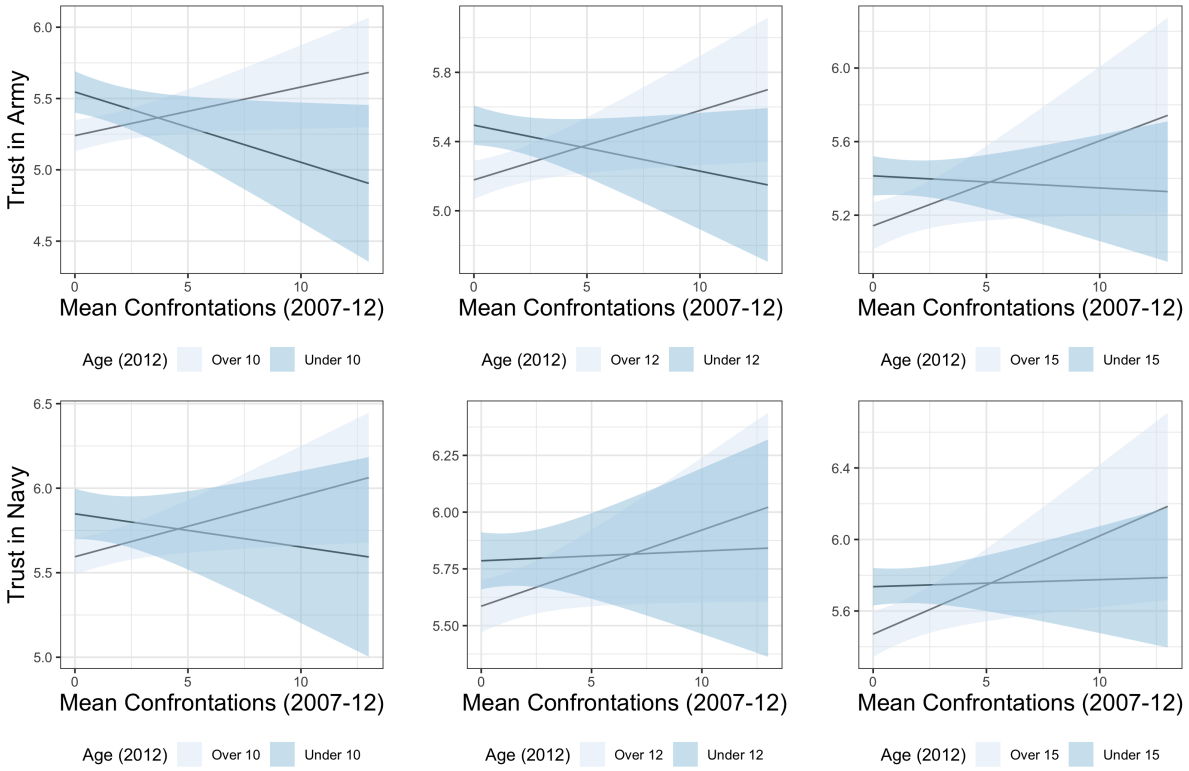


Note: trust is reported on a 1–7 scale. Mean confrontations are calculated as the average number of confrontations between the military and organized crime which each respondent was exposed to (based on their municipality of residence and birth year) for the years 2007–12. Figures present predicted values for each age group from random-intercept models with 90 per cent semi-parametric bootstrapped confidence intervals.

Source: authors' compilation.

Finally, we present visualizations regarding interpersonal trust in Figure 6. We do not find a significant, differential effect of exposure to militarization on trust in family based on respondents' age. However, we do find a significant and negative relationship between militarization and trust in the family among those who were younger than ten in 2012. However, this negative effect is not dramatic compared to previous results, and trust in the family is still predicted to be quite high (over 6 on the 1–7 scale). An increase in militarization exposure from 0 to the maximum value is associated with a 7 per cent decrease in trust. This effect disappears as we explore slightly older cohorts.

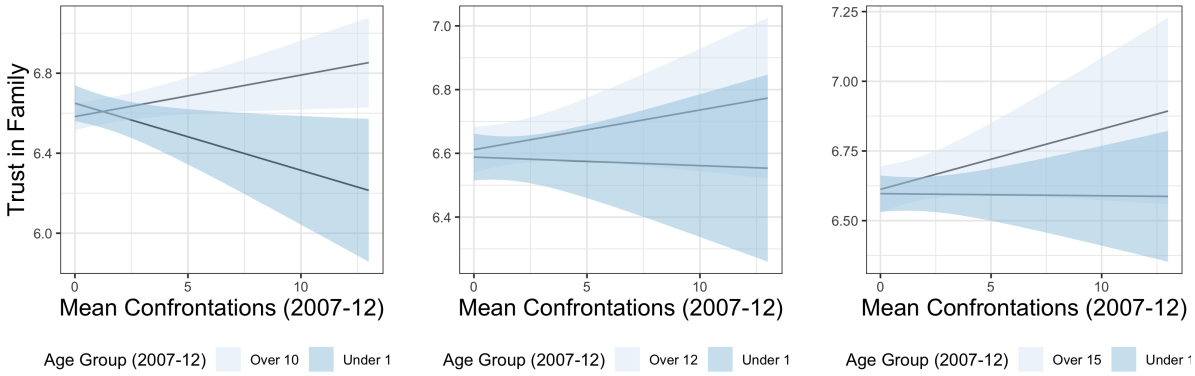
Figure 5: Predicted values of trust in military vs mean municipal military confrontations (2007–12) by age group



Note: trust is reported on a 1–7 scale. Mean confrontations are calculated as the average number of confrontations between the military and organized crime which each respondent was exposed to (based on their municipality of residence and birth year) for the years 2007–12. Figures present predicted values for each age group from random-intercept models with 90 per cent semi-parametric bootstrapped confidence intervals.

Source: authors' compilation.

Figure 6: Predicted values of interpersonal trust vs mean municipal military confrontations (2007–12) by age group



Note: trust is reported on a 1–7 scale. Mean confrontations are calculated as the average number of confrontations between the military and organized crime which each respondent was exposed to (based on their municipality of residence and birth year) for the years 2007–12. Figures present predicted values for each age group from random-intercept models with 90 per cent semi-parametric bootstrapped confidence intervals.

Source: authors' compilation.

6 Discussion

We set out to determine the degree to which violence during Mexico's Drug War has impacted both political and community trust among those who grew up during this conflict. We sought to isolate how exposure to (1) general violence and (2) internal militarization by the Mexican government affected

expressed levels of trust. With regard to general violence, we extended previous literature which often found a robust negative relationship between violence and trust to determine if this relationship existed specifically when exposure occurred during one's formative years. Further, we moved past considerations of general violence to examine if exposure to militarized internal conflict—where violence was carried out by the state across the country—would similarly impact their levels of trust.

Overall, we find strong evidence that exposure to violence, measured by homicide rates, during one's formative years has a negative impact on trust. Importantly, this effect is quite strong for almost all law enforcement agencies involved in combating organized crime during the Drug War (federal, state, and municipal police and the army). However, it does not seem that exposure to homicides greatly or consistently impacts trust in the government. This brings a nuanced new perspective to the impact of violence on trust, in light of previous research which has often found widespread negative relationships between violence exposure and political trust. Possibly, individuals exposed during their youth are less trustful of law enforcement either because they believe these groups led to higher levels of violence and/or were ineffective in protecting their communities. Particularly with regard to the police, it is likely that the latter explanation is true. According to Pion-Berlin and Carreras (2017), across Latin America citizens tend to believe the police are highly ineffective. Thus, these results suggest those exposed to higher levels of violence during their youth likely perceive law enforcement to be particularly ineffective, leading to low levels of trust later in life. However, this perception of inefficacy seems to be divorced from perceptions of the government generally speaking.

Exposure to violence during one's childhood has a consistent, negative effect on interpersonal trust, reinforcing previous work such as that of Salmi et al. (2007). However, our study demonstrates that the erosion of interpersonal trust is a long-lasting effect. While previous research demonstrates that exposure to violence can have short-term effects on trust, including among youths, ours demonstrates that this can continue to affect individuals as they age.

Moving beyond general violence, we explore how trust is affected by exposure to militarized conflict between the state and organized crime during one's youth. In this analysis we find evidence that trust is strongly reduced in actors directly tied to the Drug War. In particular, there are strong negative associations between exposure and trust in the federal police, the federal government, the state government, the army, and the navy. While we know the federal police, army, and navy were directly involved as the militarized forces (Felbab-Brown 2014; Flores-Macías 2018), it is notable that respondents draw an association between militarized conflict and the federal and state governments. While the Drug War was largely a federal government initiative, the central authorities often worked in concert with state actors to root out organized crime (Trejo and Ley 2016). Within this analysis, we also revealed a slightly unexpected pattern—exposure to militarized conflict for those above certain age thresholds seems to be associated with *increased* political trust in some cases. For example, among those over the age of 15 in 2012, trust in all levels of government increases as exposure to militarization increases. Perhaps slightly older individuals made a positive connection between militarization and government action to combat drug trafficking.

We also find some evidence of exposure to militarization and decreased trust in family. This effect could be a result of spillover violence and may reinforce the negative association between exposure to homicide and interpersonal trust. However, in all cases where we explore interpersonal trust, it is worth noting that although we often find significant effects, reported trust remains extremely high. While we find that militarization does decrease trust in the family among young individuals, they continue to trust their family much more compared to both their neighbours and political entities. Although it is concerning that levels of trust decrease, and reinforces the idea that exposure to militarized conflict can harm the social fabric of communities, we find that trust in one's family is still relatively resilient.

7 Conclusion

In this study we have provided empirical evidence of the sociopolitical effects of exposure to violence and militarization during one's youth. We contend this phenomenon remains understudied and deserves more attention in political science. We show that, within the context of Mexico's Drug War, exposure to organized criminal violence and military confrontations during childhood influences a variety of sociopolitical attitudes, including community trust and political trust. Millions of youths in Mexico have experienced heightened exposure to violence, depending on their geographic location and birth year. But little yet is known about what political and social ramifications such exposure may have on the formation of political beliefs and, more broadly, on the consolidation of Mexico's young democracy.

Our analysis sheds light on some ramifications of childhood exposure to criminal violence. We find differential effects based on the type of exposure. Exposure to homicidal violence during one's formative years has an overall negative impact on multiple political and interpersonal trust measures. However, when exploring the effects of militarization, we find that the strongest negative effects of exposure to military confrontations on institutional trust are observed among institutions largely involved in Mexico's Drug War, such as the federal police, the federal and state governments, and the army.

These findings suggest that exposure to violence during one's youth has long-lasting effects, and can affect the social fabric of a society going forward. This is of paramount importance for understanding the political landscape of modern-day Mexico, as many young individuals are victims of heightened violence. The broader implications of our research are relevant to several countries in Latin America and the Global South where youths have been exposed to protracted violence within their communities. Various paths remain open for future research. Further contributions are needed to improve our understanding of whether different types of exposure to violence during childhood are associated with the adoption of certain political ideologies in adult life, and whether the impacts on trust and political engagement persist over time.

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Appendix

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A Survey protocols

Our survey was fielded in partnership with our local partner, Buendía & Marquez, based in Mexico City, Mexico. The survey was fielded as part of the larger Performance Evaluation of USAID/Mexico's Crime and Violence Prevention Activity. The survey was reviewed by the Institutional Review Board at George Washington University and received approval (FWA00005945). The study was conducted in compliance with all local Mexican laws and regulations, in addition to ethical standards contained in the 1964 Declaration of Helsinki, including its amendments.

A1 Survey format and recruitment

The survey was conducted face-to-face with structured questionnaires by trained interviewers who used personal tablets. Interviewers followed all local COVID-19 protocols and maintained social distance from interviewees. Once a survey was complete, responses were immediately uploaded to the cloud and removed from the tablet to ensure sensitive information would not be at risk of disclosure. All completed questionnaires were checked during and after fieldwork for quality control. Interviewers also worked in teams of three with a supervisor whose responsibility was to monitor quality and make any necessary adjustments.

To recruit survey participants, enumerators followed a random selection process detailed in the following section. Once participants were selected, the enumerator invited a participant in the household to participate in the survey completely voluntarily. Subjects were told they could decline to participate or end their participation in the survey at any time. Enumerators required verbal consent to participate from the respondents following a consent text. Consent was not requested from parents, as we did not interview youths under the age of 16. Participants may have responded differently (and bias results) during interviews if they knew their parents needed to consent. Further, some answers regarding behaviour among youth, such as entertainment and attitudes towards crime in the community, were likely to be influenced by parental approval.

We did not offer compensation for participation in the survey, which is standard among short in-person surveys in the region (e.g., the Latin American Public Opinion Project at Vanderbilt University). Surveys took on average about 20 minutes of respondents' time. Although respondents were not offered monetary compensation, they were told of the possible benefits of participation. These included voicing concerns regarding violence in their communities and how the results from our study could help develop a deeper understanding regarding insecurity dynamics in the localities where the surveyed individuals live. The project was also conducted in conjunction with USAID and was aimed to better design crime prevention efforts in Mexico, which would positively impact research subjects.

No methods of deception were included in our survey, nor was identifiable information collected regarding any of the participants. The research involved no more than minimal risk to subjects, the investigators, and research staff apart from possible discomfort when responding to some questions. However, participants were warned of this risk and the consent process emphasized the option for respondents to end the survey at any time if they wished.

A2 Sampling design

The survey was designed to achieve a nationally representative sample of urban Mexico for ages 16–29. In addition, the survey was designed to be representative of certain security realities (homicide, perceived insecurity, and victimization). To do so, a multistage area probability sampling design was used. Respondents were selected using a four stage sampling process. Stage 1 involved the selection of primary sampling units (PSUs), which in this case were electoral sections—a small geographic ju-

risdiction in Mexico that is smaller than the municipality. They constitute the basic territorial unit of single-member electoral districts for citizens to register to vote. As of March 2021, Mexico was divided into 68,806 electoral sections.

To select PSUs, the sampling frame was limited to Mexican municipalities which were covered by the Encuesta Nacional de Seguridad Pública Urbana (ENSU, National Urban Public Security Survey) run by Mexico's national statistical institute, the Instituto Nacional de Estadística y Geografia (INEGI). This survey is representative of urban Mexico and includes important public security information that was used later in the sampling process. From this, the number of PSUs eligible to be included in our survey was reduced to 30,878. We supplemented this list of municipalities and PSUs with additional information from the November 2020 Geoelectoral Information Catalog from INEGI and the 2020 census to create our final sampling frame.

We supplemented the sampling frame with additional information regarding three measures of security realities in Mexico. We added three municipal-level measures of violence. These were homicide rates as reported by the Executive Secretariat of the National System of Public Security (SESNSP), a measure of perceived community security, and a measure of victimization. In Mexico, homicide data are available from two sources—via the SESNSP reflecting police investigations and via INEGI from death certificates. Although INEGI data tends to be more precise, the publication of this data is usually delayed by over a year. Because of this, we used SESNSP data which covered the entirety of 2020 at the municipal level. We only used data regarding intentional homicides.

The latter two measures were generated using responses from the ENSU survey. Given that the ENSU data are not representative at the municipal level, we generated municipal estimates using multilevel regression and post-stratification (MRP). To do so, we brought in additional information from the 2015 intercensus. These measures capture the preponderance of non-homicidal crime (victimization) and perceived community insecurity at the municipal level. In particular, we used the following questions from the ENSU survey:

- **Perceived security**: In terms of crime, do you consider that to live in (CITY) currently is … [safe, unsafe]? *En términos de la delincuencia, ¿considera que vivir actualmente en (CIUDAD), es … [seguro, inseguro]?*

- **Victimization**: During the past year [insert year], that is to say from January to today, has a member of your household (including yourself) been victim of (INSERT TYPE OF CRIME) on card A? *Durante este año [insert year], es decir, de enero a la fecha, ¿algún integrante de este hogar incluido usted, sufrieron la situación (CÓDIGO DE INCIDENCIA) de la tarjeta A?*

  - Robbery or assault in the street or in public transportation? Yes or No? *Robo o asalto en la calle o en el transporte público (incluye robo en banco o cajero automático)? Sí o No?*

  - Threats, pressure, or deception to demand money or goods or to do something/not to do something (extortion, blackmail)? Yes or No? *Amenazas, presiones, o engaños para exigir dinero o bienes; o para que hiciera algo o dejara de hacerlo (extorsión)? Sí o No?*

For the first measure, perceived security, we coded the variable as 1 if an individual reported feeling 'insecure' and 0 if an individual reported feeling 'secure' in their city. For our second measure, victimization, we coded the variable as 1 if the individual reported that a member of their household had either experienced robbery or extortion in the past year and coded 0 if not.

With these questions, we then estimated the relationship between various individual-level characteristics and their responses on these selected survey questions. We did this through multilevel regression, where we determined the relationship between selected characteristics—in this case age, gender, education,

and occupation—and reported (i) insecurity and (ii) household victimization. This involved two separate regression models, one for each outcome variable. The regression also factored in geographic location, with individuals' municipalities (unrepresentative unit of interest) nested within their states (geographic unit of the survey).

Once these regression estimates were calculated, we then post-stratified them. This involved weighting our estimates by the prevalence of each type of individual within each municipality based on their individual-level characteristics (i.e., age, education, etc.). This 'prevalence' was calculated by determining the population of each type of individual within a municipality according to the 2015 intercensus. The regression estimates, weighted in this manner, generated a municipal-level estimate (one for each municipality) for the most likely response to each of the two survey questions.

Through this process, we calculated two municipal-level estimates: one quantifying non-homicidal victimization and the other quantifying residents' perception of community security in their municipality. We calculated these values for all municipalities included in the most recent ENSU survey, yielding estimates for 157 municipalities. These values can be interpreted as a ranking of perceived security and victimization among the municipalities we examined. They allowed us to determine within our sample of municipalities how they rank comparatively in terms of these two values. However, these measures do have errors associated with them and cannot be compared to estimates outside of these analyses. This error was predominantly created by limitations due to question wording and the need to match variables between the census and survey. We had to match individual-level responses on the ENSU survey to biographical information about the head of household, as certain attributes were only recorded at the head-of-household level (e.g., education level, occupation) in this survey. We used these head-of-household characteristics when considering the prevalence of each type of individual in the intercensus. Thus, these measures are not perfect individual-level measures, but did provide us with comparable inter-sample estimates. For this reason, we interpreted them as a ranking. For more information regarding the MRP indicators, see Appendix B.

These measures were then added to our sampling frame for their corresponding municipalities and PSUs. Our sample of PSUs were then selected for the sample through a systematic method of stratified probability proportional to size (PPS). Each PSU in the sampling frame was also assigned a non-overlapping sample stratum based on the three security variables. We combined PPS with a systematic sampling approach and used implicit stratification (via a travelling salesperson algorithm) based on the three violence measures. Survey sample strata information can be seen in Table A1. In total, 288 PSUs were selected and ten interviews were conducted in each PSU.

Table A1: Strata information for sample frame and sample

Strata	Frame mun. #	Frame mun. proportion	Frame pop.	Frame pop. proportion	Sample mun. #	Sample mun. prop.	Sample pop.	Sample pop. prop.
High-Low-Low	1	0.006	18812	0.000	1.000	0.009	768.000	0.001
High-High-High	12	0.076	3624341	0.080	9.400	0.087	77308.600	0.086
High-High-Low	28	0.178	11204188	0.246	24.200	0.225	228749.000	0.257
Med-Low-Low	10	0.064	1641492	0.036	5.000	0.046	39381.600	0.044
Med-High-High	19	0.121	8489648	0.187	15.200	0.141	126626.200	0.142
Med-High-Low	11	0.070	5328138	0.117	7.400	0.069	108716.000	0.122
Low-Low-High	1	0.006	231209	0.005	1.000	0.009	5381.600	0.006
Low-Low-Low	46	0.293	8313862	0.183	28.200	0.262	181206.000	0.203
Low-High-High	15	0.096	3192100	0.070	8.400	0.078	50260.000	0.057
Low-High-Low	14	0.089	3418396	0.075	8.600	0.080	73078.400	0.082

Note: strata listed in terms homicide rate, perceived insecurity, and reported victimization from left to right.

Within each stratum available, electoral precincts, our primarily sampling units (PSU) were chosen based on the probability proportional to each precinct's size (PPS). In all, 288 electoral sections were selected from the sampling frame and ten interviews were conducted in each.

In some cases, PSUs were not available to conduct interviews due to various circumstances, including security concerns for interviewers. In such cases, a new PSU with the same stratum characteristics and probability of selection was drawn from an independent sample.

With this sample of PSUs, area segments sampling was then used to select second-stage sampling units (SSUs). We used blocks as our SSUs, or geographic spaces delimited by streets or avenues. SSUs were identified and assigned to interviews using maps from the Instituto Nacional Electoral (INE, National Electoral Institute). Within each PSU, two SSUs were selected via a random sample from INE's Catálogo de Manzanas (a catalog of small geographic subdivisions called 'manzanas').

Once the SSUs were selected, housing units were then chosen which represented our final sampling unit. Five interviews were conducted per SSU. Housing units were selected via a spiral method and clockwise walking. Interviewers cover each block by starting at the northeast corner and use a sampling interval of three housing units. Once an interview is completed, the interviewer moves to the other side of the block, ensuring that only one interview is conducted on each side of the block. Then, interviewers moved to an adjacent block using the spiral method. In multi-story buildings, the same process was utilized but only when a building occupies a whole block. If a building is located on one side of the block, only one interview may take place inside the building. After such an interview, interviewers must move on from both the building and side of the block.

Once housing units were selected, an individual was then selected by the interviewer. A short screening interview was conducted with a knowledgeable adult to determine if members of the household meet the study eligibility criteria. With the information provided by the present adult, the tablet then picked a respondent from the total pool of eligible household inhabitants. The interviewer then asked to speak to that individual.

In total, 64 interviewers were used to complete the survey. 2,880 interviews were completed over nine days between 12 and 20 June 2021.

B MRP goodness of fit indicators

In this section, we demonstrate information which confirms the adequacy of our MRP indicators. First, we demonstrate the correlations between our two MRP measures and the true values (means) of the variables we used to create these measures (victimization and perceived security). High, but not perfect, correlation would indicate a strong MRP estimate. This is shown in Figure A1, which confirms that our MRP estimates and the true values are highly correlated (for those municipalities for which we had a representative estimator). We also see a correlation between homicide rates and MRP insecurity perception estimates, but a nearly zero correlation between homicide rates and MRP victimization estimates. We observe a high correlation between MRP security and victimization estimates.

Figure A1: Correlations between MRP estimates and true values (means)

Source: authors' elaboration; reproduction of Appendix Figure I in Bronsoler Nurko et al. (2021: 74).

To further explore these results, we ran mixed-effects models with random intercepts by state. Results are shown in Figure A2, on which population, homicide, and homicide rate are rescaled as values ranging from 0 to 1.

For the security measures in Figure A2, as the population increases, so does insecurity. As the homicide rate increases, so does the insecurity index. Total homicide does not have a significant relationship with this index. In terms of the victimization index, there is little relationship with the included variables (the coefficient sizes are very small and confidence intervals cross zero). As population increases, the victimization index increases slightly. However, total homicide and homicide rate do not have significant relationships with victimization index, as confidence intervals include zero in both cases. From this analysis, we observe that in urban Mexico, there are places with homicide violence but not much other violence and vice versa, and there does seem to be little correlation between homicide rates and victimization estimates. There are correlations between homicide rates and security perceptions, although these are not high. Therefore, we divided the sampling units (using the ENSU sample) by levels of homicide, non-homicidal violence (victimization), and insecurity perception.

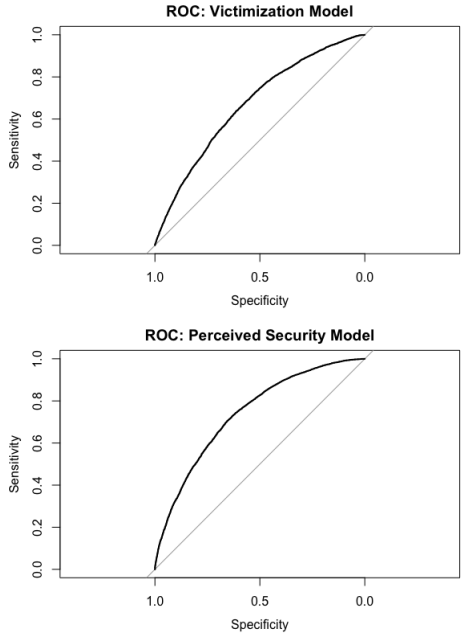
Figure A2: Correlations between MRP estimates and true values (means)

	Security 2020			Vic. 2020		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
Intercept	5.88	-20.14 – 31.90	0.658	5.62	-1.32 – 12.57	0.113
Log Population	4.03	2.00 – 6.06	**<0.001**	0.69	0.17 – 1.22	**0.010**
Hom. Total	6.32	-20.92 – 33.56	0.649	1.40	-5.85 – 8.65	0.705
Hom. Per 100k	28.13	7.67 – 48.59	**0.007**	1.44	-4.09 – 6.97	0.610
Random Effects						
σ^2	106.15			6.74		
τ_{00}	181.22 $_{state\_code}$			31.08 $_{state\_code}$		
ICC	0.63			0.82		
N	32 $_{state\_code}$			32 $_{state\_code}$		
Observations	157			157		
Marginal R^2 / Conditional R^2	0.208 / 0.708			0.036 / 0.828		

Source: authors' elaboration; reproduction of Appendix Table I in Bronsoler Nurko et al. (2021: 74).

Below, Figure A3 provides ROC (receiver operating characteristic) curves for the multi-level models used in the MRP process. These curves demonstrate the ability of the models to correctly predict outcomes, with the x-y line indicating a 'null model'. It can be considered a measure of sensitivity (probability of detection) versus specificity (probability of false detection) and is essentially a plot of the model's power as a function of Type 1 error (rejection of true null hypothesis, false positive). Both plots below indicate the models perform better than the null model, providing evidence of their strength for prediction of both outcomes of interest (victimization and perceived security).

Figure A3: Receiver operating characteristic curves for multilevel models



Source: authors' elaboration.

C Survey descriptive statistics

Table A2: Sex, age, and education breakdown

Sex	Mean age	Mode edu	Num. respondents
Male	21.47	Preparatoria o bachillerato	1326
Female	22.38	Preparatoria o bachillerato	1554

Table A3: Employment status in the past week

Type	% Respondents
Worked	43.5
Had a job but did not work	1.8
Looked for work	5.5
Student	25.8
Household work	15.6
Permanently incapacitated	0.7
Did not work	6.3
No response	1.0

Table A4: Economic indicators

	Marginalization	SES
Minimum	-2.23	0.00
Mean	-1.59	1.94
Maximum	-0.20	2.56

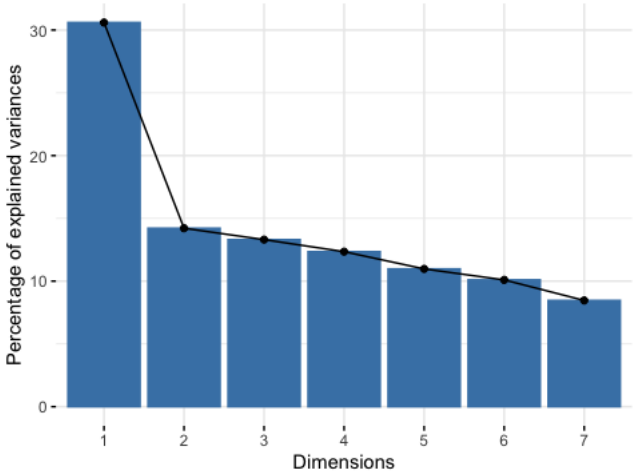
D Socioeconomic status variable creation

To create the variable which we use to measure socioeconomic status (SES), we rely on a battery of questions regarding the possession of certain material goods (see Table A5). We then use these questions to create one variable measuring SES using principal component analysis (PCA). We use the first calculated component which explains the most variance (over 30%) across participants (see Figure A4). Not all participants responded to each question regarding possession of each good—to fill in these gaps, we used multiple imputation using predictive mean matching (PMM) (see Heitjan and Little 1991; Little 1988), implemented via the Multiple Imputation by Chained Equations (MICE) package in R (Van Buuren and Groothuis-Oudshoorn 2011). This process resulted in a variable which has a maximum value of 2.56, minimum value of 0, and mean value of 1.94.

Table A5: Items included in socioeconomic status variable and descriptive statistics

Please tell me if you or a member of your household has CURRENT access to each of the following services in your home (Yes = 1, No = 0):	**Minimum**	**Median**	**Mean**	**Max**	**NAs**
Car	0	1	0.58	1	21
Clothes washer	0	1	0.88	1	22
Indoor plumbing	0	1	0.94	1	24
Computer	0	1	0.64	1	23
Internet	0	1	0.87	1	26
Cell phone	0	1	0.94	1	22
Domestic worker	0	0	0.26	1	27

Figure A4: PCA variance explained



Source: authors' elaboration.

E Identification strategy

First, we explore the effect of exposure to homicidal violence on trust. We specify our model as a linear model with non-nested random intercepts for both year and municipality as follows:

$$y_i = \beta_1 V_i + \beta_2 X_i + \alpha_{j[i]} + \gamma_{k[i]} + \epsilon_i \tag{1}$$

$$\alpha_j \sim N(0, \sigma_\alpha^2) \tag{2}$$

$$\gamma_k \sim N(0, \sigma_\gamma^2) \tag{3}$$

In this model, α and γ represent the non-nested random intercepts for the j municipalities and k birth years in our sample. Further, y_i is the outcome of interest (trust) and i is each individual respondent. X_i is a vector of individual-level control covariates. These are gender, socioeconomic status, and education level.[1] The parameter of interest is β_2, where V_i represents childhood exposure to violence, measured as an average of the homicide rate in the individual's municipality between their birth year and their tenth year of life. For example, the mean childhood exposure to violence during ages 0 to 10, for two respondents born in the same municipality in years t and $t+1$, is computed as the average homicide rate in years (t,...,t+10) and (t+1,...,t+11), respectively.

[1] To create our socioeconomic status control variable, we rely upon a series of survey questions which determine respondents' possession of a series of assets. We then use principal component analysis (PCA) to create this variable.

To test the role of militarization on trust, we adapt this modeling strategy slightly to incorporate whether or not a respondent was older or younger than one of three age cut-offs (10, 12, and 15) in 2012 and interact this variable with exposure to militarization. Following this logic, we model this relationship as follows:

$$y_i = \beta_1 M_i + \beta_2 D_i + \beta_3 M_i D_i + \beta_4 X_i + \alpha_{j[i]} + \gamma_{k[i]} + \epsilon_i \tag{4}$$

$$\alpha_j \sim N(0, \sigma_\alpha^2) \tag{5}$$

$$\gamma_k \sim N(0, \sigma_\gamma^2) \tag{6}$$

Once again, α and γ represent the non-nested random intercepts for the j municipalities and k birth years. y_i and i remain as our outcome of interest and each individual respondent, respectively. M_i represents the average number of military confrontations between 2007 and 2012 for each respondent, calculated based on both their age and municipality of residence. D_i is a dummy variable which is equal to 1 if the respondent was 10 years, 12 years, or 15 years or older in 2012, and 0 if not. Our estimand of interest is β_3, which captures the interaction effect between M_i and D_i and indicates whether or not there is a different effect of militarization based on a respondent's age group in 2012. Once again, X_i represents a vector of control covariates, which are the same as those used in our previous model.

F Additional models

F1 Exposure to homicide main results

Here we provide all coefficients from our main models regarding exposure to homicide. Figures for statistically significant results from these models are presented in the main text.

Table A6: Average exposure to homicides and trust in police

	Dependent variable:		
	Federal	State	Municipal
	(1)	(2)	(3)
Avg exposure 0-10 yrs	-0.012^{***}	-0.006^{*}	-0.010^{**}
	(0.004)	(0.004)	(0.004)
Male	0.068	0.026	0.094
	(0.069)	(0.068)	(0.068)
SES	-0.170^{**}	-0.070	-0.041
	(0.071)	(0.070)	(0.070)
Edu	-0.068^{***}	-0.030	-0.016
	(0.020)	(0.020)	(0.020)
Constant	5.672^{***}	4.100^{***}	3.593^{***}
	(0.162)	(0.161)	(0.173)
Mun. RE	Yes	Yes	Yes
Age RE	Yes	Yes	Yes
Observations	2,405	2,407	2,407
Log likelihood	$-4,648.293$	$-4,628.556$	$-4,638.777$
Akaike inf. crit.	9,312.585	9,273.112	9,293.554
Bayesian inf. crit.	9,358.868	9,319.401	9,339.843
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table A7: Average exposure to homicides and interpersonal trust

	Dependent variable:	
	Family	Neighbours
	(1)	(2)
Avg exposure 0-10 yrs	-0.006^{***}	-0.011^{**}
	(0.002)	(0.004)
Male	0.095^{**}	0.346^{***}
	(0.042)	(0.076)
SES	0.134^{***}	0.159^{**}
	(0.043)	(0.078)
Edu	0.030^{**}	0.123^{***}
	(0.012)	(0.022)
Constant	6.074^{***}	3.048^{***}
	(0.095)	(0.172)
Mun. RE	Yes	Yes
Age RE	Yes	Yes
Observations	2,410	2,407
Log likelihood	−3,490.952	−4,887.949
Akaike inf. crit.	6,997.905	9,791.897
Bayesian inf. crit.	7,044.204	9,838.187
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table A8: Average exposure to homicides and trust in military

	Dependent variable:	
	Army	Navy
	(1)	(2)
Avg exposure 0-10 yrs	-0.008^{**}	−0.006
	(0.004)	(0.004)
Male	0.266^{***}	0.352^{***}
	(0.065)	(0.064)
SES	-0.183^{***}	-0.169^{**}
	(0.067)	(0.066)
Edu	-0.035^{*}	−0.025
	(0.019)	(0.019)
Constant	5.706^{***}	5.855^{***}
	(0.152)	(0.149)
Mun. RE	Yes	Yes
Age RE	Yes	Yes
Observations	2,408	2,394
Log likelihood	−4,531.657	−4,452.200
Akaike inf. crit.	9,079.315	8,920.401
Bayesian inf. crit.	9,125.607	8,966.646
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table A9: Average exposure to homicides and trust in government

	Dependent variable:		
	Federal	State	Municipal
	(1)	(2)	(3)
Avg exposure 0-10 yrs	-0.006	-0.005	-0.008^{**}
	(0.004)	(0.004)	(0.004)
Male	0.203^{***}	0.198^{***}	0.177^{***}
	(0.069)	(0.069)	(0.069)
SES	-0.116	-0.208^{***}	-0.132^{*}
	(0.072)	(0.070)	(0.071)
Edu	-0.060^{***}	-0.019	-0.051^{**}
	(0.020)	(0.020)	(0.020)
Constant	4.834^{***}	4.305^{***}	4.216^{***}
	(0.163)	(0.163)	(0.173)
Mun. RE	Yes	Yes	Yes
Age RE	Yes	Yes	Yes
Observations	2,402	2,406	2,410
Log likelihood	$-4,672.737$	$-4,647.954$	$-4,660.378$
Akaike inf. crit.	9,361.473	9,311.908	9,336.756
Bayesian inf. crit.	9,407.746	9,358.194	9,383.055
Note:	*p$<$0.1; **p$<$0.05; ***p$<$0.01		

F2 Exposure to homicide: controlling for recent homicide rate

Although the inclusion of random intercepts for both municipality and birth year should account for variation in the homicide rate closer to the administration of our survey, we include models here with a homicide rate control (homicide per 100k citizens) for 2020. All results all directionally consistent with results provided in the main text.

Table A10: Average exposure to homicides and trust in police

	Dependent variable:		
	Federal	State	Municipal
	(1)	(2)	(3)
Avg exposure 0-10 yrs	-0.009^{**}	-0.003	-0.007
	(0.004)	(0.004)	(0.004)
Hom 100k	-0.003	-0.003	-0.003
	(0.002)	(0.002)	(0.002)
Male	0.068	0.028	0.095
	(0.069)	(0.068)	(0.068)
SES	-0.170^{**}	-0.066	-0.040
	(0.071)	(0.070)	(0.070)
Edu	-0.070^{***}	-0.033^{*}	-0.019
	(0.020)	(0.020)	(0.020)
Constant	5.734^{***}	4.145^{***}	3.651^{***}
	(0.166)	(0.162)	(0.176)
Mun. RE	Yes	Yes	Yes
Age RE	Yes	Yes	Yes
Observations	2,405	2,407	2,407
Log likelihood	$-4,652.427$	$-4,632.859$	$-4,642.875$
Akaike inf. crit.	9,322.854	9,283.717	9,303.750
Bayesian inf. crit.	9,374.921	9,335.793	9,355.825
Note:		*p$<$0.1; **p$<$0.05; ***p$<$0.01	

Table A11: Average Exposure to homicides and trust in military

	Dependent variable:	
	Army	Navy
	(1)	(2)
Avg exposure 0-10 yrs	-0.008^{*}	-0.005
	(0.004)	(0.004)
Hom 100k	-0.0004	-0.002
	(0.002)	(0.002)
Male	0.266^{***}	0.352^{***}
	(0.065)	(0.064)
SES	-0.183^{***}	-0.169^{**}
	(0.067)	(0.066)
Edu	-0.035^{*}	-0.026
	(0.019)	(0.019)
Constant	5.713^{***}	5.886^{***}
	(0.156)	(0.153)
Mun. RE	Yes	Yes
Age RE	Yes	Yes
Observations	2,408	2,394
Log likelihood	$-4,537.025$	$-4,457.220$
Akaike inf. crit.	9,092.050	8,932.441
Bayesian inf. crit.	9,144.129	8,984.467
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table A12: Average exposure to homicides and trust in government

	Dependent variable:		
	Federal	State	Municipal
	(1)	(2)	(3)
Avg exposure 0-10 yrs	-0.005	-0.005	-0.004
	(0.005)	(0.004)	(0.004)
Hom 100k	-0.002	0.00003	-0.004^{**}
	(0.002)	(0.002)	(0.002)
Male	0.204^{***}	0.197^{***}	0.179^{***}
	(0.069)	(0.069)	(0.069)
SES	-0.116	-0.208^{***}	-0.129^{*}
	(0.072)	(0.070)	(0.071)
Edu	-0.061^{***}	-0.019	-0.054^{***}
	(0.020)	(0.020)	(0.020)
Constant	4.867^{***}	4.305^{***}	4.287^{***}
	(0.168)	(0.166)	(0.175)
Mun. RE	Yes	Yes	Yes
Age RE	Yes	Yes	Yes
Observations	2,402	2,406	2,410
Log likelihood	$-4,677.663$	$-4,653.398$	$-4,663.685$
Akaike inf. crit.	9,373.326	9,324.797	9,345.370
Bayesian inf. crit.	9,425.383	9,376.868	9,397.456
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table A13: Average exposure to homicides and interpersonal trust

	Dependent variable:	
	Family	Neighbours
	(1)	(2)
Avg exposure 0-10 yrs	-0.009^{***}	-0.012^{***}
	(0.002)	(0.005)
Hom 100k	0.003^{***}	0.001
	(0.001)	(0.002)
Male	0.095^{**}	0.346^{***}
	(0.042)	(0.076)
SES	0.135^{***}	0.160^{**}
	(0.043)	(0.078)
Edu	0.032^{***}	0.124^{***}
	(0.012)	(0.022)
Constant	6.018^{***}	3.024^{***}
	(0.096)	(0.176)
Mun. RE	Yes	Yes
Age RE	Yes	Yes
Observations	2,410	2,407
Log likelihood	$-3,492.644$	$-4,893.006$
Akaike inf. crit.	7,003.287	9,804.011
Bayesian inf. crit.	7,055.374	9,856.086
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$	

F3 Exposure to homicide: two-way fixed effects models

Below are results from an alternative model specification, using two-way fixed effects for both municipality and birth year of respondents. Results are directionally consistent with our main results.

Table A14: Average exposure to homicides and trust in police

	Dependent variable:		
	Federal	State	Municipal
	(1)	(2)	(3)
Avg Exposure 0-10 yrs	-0.016^{***}	-0.008	-0.011^{*}
	(0.006)	(0.006)	(0.006)
Male	0.079	0.005	0.079
	(0.070)	(0.070)	(0.070)
SES	-0.165^{**}	-0.113	-0.114
	(0.074)	(0.074)	(0.073)
Edu	-0.063^{***}	-0.026	-0.011
	(0.021)	(0.021)	(0.021)
Constant	5.398^{***}	3.817^{***}	3.406^{***}
	(0.342)	(0.340)	(0.340)
Mun. FE	Yes	Yes	Yes
Age FE	Yes	Yes	Yes
Observations	2,405	2,407	2,407
R^2	0.091	0.072	0.093
Adjusted R^2	0.044	0.023	0.045
Residual Std. Error	1.645 (df = 2284)	1.636 (df = 2286)	1.635 (df = 2286)
F Statistic	1.915^{***} (df = 120; 2284)	1.468^{***} (df = 120; 2286)	1.946^{***} (df = 120; 2286)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A15: Average exposure to homicides and interpersonal trust

	Dependent variable:	
	Family	Neighbours
	(1)	(2)
Avg Exposure 0-10 yrs	-0.006	-0.016^{**}
	(0.004)	(0.007)
Male	0.097^{**}	0.328^{***}
	(0.043)	(0.078)
SES	0.133^{***}	0.096
	(0.046)	(0.082)
Edu	0.036^{***}	0.114^{***}
	(0.013)	(0.023)
Constant	6.358^{***}	3.078^{***}
	(0.213)	(0.379)
Mun. FE	Yes	Yes
Age FE	Yes	Yes
Observations	2,410	2,407
R^2	0.067	0.096
Adjusted R^2	0.019	0.049
Residual Std. Error	1.023 (df = 2289)	1.824 (df = 2286)
F Statistic	1.380^{***} (df = 120; 2289)	2.030^{***} (df = 120; 2286)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table A16: Average exposure to homicides and trust in military

	Dependent variable:	
	Army	Navy
	(1)	(2)
Avg Exposure 0-10 yrs	-0.006	-0.004
	(0.006)	(0.006)
Male	0.260^{***}	0.343^{***}
	(0.067)	(0.066)
SES	-0.190^{***}	-0.144^{**}
	(0.071)	(0.069)
Edu	-0.022	-0.019
	(0.020)	(0.020)
Constant	5.604^{***}	5.891^{***}
	(0.327)	(0.320)
Mun. FE	Yes	Yes
Age FE	Yes	Yes
Observations	2,408	2,394
R^2	0.079	0.082
Adjusted R^2	0.030	0.034
Residual Std. Error	1.571 (df = 2287)	1.537 (df = 2273)
F Statistic	1.625^{***} (df = 120; 2287)	1.700^{***} (df = 120; 2273)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table A17: Average exposure to homicides and trust in government

	Dependent variable:		
	Federal	State	Municipal
	(1)	(2)	(3)
Avg Exposure 0-10 yrs	-0.010	-0.012^{**}	-0.008
	(0.006)	(0.006)	(0.006)
Male	0.190^{***}	0.178^{**}	0.168^{**}
	(0.071)	(0.070)	(0.070)
SES	-0.092	-0.208^{***}	-0.180^{**}
	(0.075)	(0.074)	(0.074)
Edu	-0.053^{**}	-0.017	-0.052^{**}
	(0.021)	(0.021)	(0.021)
Constant	4.071^{***}	4.007^{***}	3.382^{***}
	(0.346)	(0.344)	(0.343)
Mun. FE	Yes	Yes	Yes
Age FE	Yes	Yes	Yes
Observations	2,402	2,406	2,410
R^2	0.089	0.076	0.097
Adjusted R^2	0.041	0.028	0.050
Residual Std. Error	1.666 (df = 2281)	1.653 (df = 2285)	1.649 (df = 2289)
F Statistic	1.851^{***} (df = 120; 2281)	1.574^{***} (df = 120; 2285)	2.046^{***} (df = 120; 2289)
Note:			*p<0.1; **p<0.05; ***p<0.01

F4 Exposure to militarization results

The following models examine an interaction between the mean number of military confrontations in a municipality and the respondent's age at that time. A dummy is created for individuals who were younger than 10, 12, or 15 in 2012 (approximately the end of the most violent period of the drug war).

Table A18: Exposure to military confrontations and trust in police

	Dependent variable:								
	Federal			State			Municipal		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Mean Confrontations	0.022	0.019	0.027	0.031*	0.017	0.045*	0.036*	0.034	0.044
	(0.022)	(0.024)	(0.029)	(0.017)	(0.019)	(0.026)	(0.020)	(0.022)	(0.028)
Younger than 10	0.302***			0.435***			0.568***		
	(0.110)			(0.094)			(0.133)		
Younger than 12		0.305***			0.362***			0.545***	
		(0.084)			(0.078)			(0.090)	
Younger than 15			0.244**			0.424***			0.534***
			(0.095)			(0.084)			(0.102)
Male	0.064	0.053	0.057	0.028	0.018	0.015	0.094	0.090	0.086
	(0.068)	(0.069)	(0.069)	(0.068)	(0.068)	(0.068)	(0.068)	(0.068)	(0.068)
SES	−0.178**	−0.183**	−0.174**	−0.075	−0.075	−0.066	−0.045	−0.043	−0.036
	(0.071)	(0.071)	(0.071)	(0.070)	(0.070)	(0.069)	(0.071)	(0.070)	(0.070)
Edu	−0.062***	−0.061***	−0.063***	−0.025	−0.031	−0.033*	−0.013	−0.018	−0.020
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Mean Conf*Younger 10	−0.118***			−0.042			−0.058*		
	(0.033)			(0.032)			(0.032)		
Mean Conf*Younger 12		−0.066**			0.008			−0.032	
		(0.029)			(0.029)			(0.029)	
Mean Conf*Younger 15			−0.054*			−0.041			−0.038
			(0.031)			(0.031)			(0.031)
Constant	5.486***	5.446***	5.422***	3.894***	3.907***	3.799***	3.347***	3.311***	3.202***
	(0.162)	(0.160)	(0.168)	(0.153)	(0.152)	(0.159)	(0.163)	(0.158)	(0.168)
Mun. RE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age RE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,405	2,405	2,405	2,407	2,407	2,407	2,407	2,407	2,407
Log Likelihood	−4,646.602	−4,648.654	−4,651.009	−4,624.834	−4,624.104	−4,623.556	−4,636.227	−4,634.087	−4,635.007
Akaike Inf. Crit.	9,313.205	9,317.308	9,322.018	9,269.668	9,268.209	9,267.112	9,292.455	9,288.174	9,290.013
Bayesian Inf. Crit.	9,371.058	9,375.161	9,379.871	9,327.529	9,326.070	9,324.973	9,350.316	9,346.036	9,347.875
Note:									*p<0.1; **p<0.05; ***p<0.01

Table A19: Exposure to military confrontations and interpersonal trust

	Dependent variable:					
	Family			Neighbours		
	(1)	(2)	(3)	(4)	(5)	(6)
Mean Confrontations	0.021*	0.012	0.022	0.031	0.035	0.029
	(0.011)	(0.013)	(0.016)	(0.022)	(0.024)	(0.030)
Younger than 10	0.067			−0.099		
	(0.058)			(0.096)		
Younger than 12		−0.023			0.005	
		(0.051)			(0.087)	
Younger than 15			−0.015			0.024
			(0.052)			(0.090)
Male	0.091**	0.092**	0.094**	0.342***	0.337***	0.333***
	(0.042)	(0.042)	(0.042)	(0.076)	(0.076)	(0.076)
SES	0.130***	0.137***	0.135***	0.171**	0.160**	0.156**
	(0.044)	(0.044)	(0.043)	(0.078)	(0.078)	(0.078)
Edu	0.033***	0.030**	0.032**	0.118***	0.125***	0.127***
	(0.012)	(0.012)	(0.012)	(0.022)	(0.022)	(0.022)
Mean Conf*Younger 10	−0.054***			−0.029		
	(0.020)			(0.036)		
Mean Conf*Younger 12		−0.015			−0.027	
		(0.018)			(0.032)	
Mean Conf*Younger 15			−0.022			−0.008
			(0.019)			(0.034)
Constant	5.989***	6.021***	6.016***	2.969***	2.912***	2.894***
	(0.096)	(0.096)	(0.100)	(0.173)	(0.173)	(0.178)
Mun. RE	Yes	Yes	Yes	Yes	Yes	Yes
Age RE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,410	2,410	2,410	2,407	2,407	2,407
Log Likelihood	−3,493.998	−3,497.108	−3,496.705	−4,891.302	−4,892.667	−4,892.953
Akaike Inf. Crit.	7,007.997	7,014.216	7,013.410	9,802.604	9,805.334	9,805.907
Bayesian Inf. Crit.	7,065.871	7,072.090	7,071.284	9,860.465	9,863.195	9,863.768
Note:						*p<0.1; **p<0.05; ***p<0.01

Table A20: Exposure to military confrontations and trust in government

	Dependent variable:								
	Federal			State			Municipal		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Mean Confrontations	0.036	0.032	0.044	0.046***	0.049***	0.054**	0.052***	0.046**	0.073***
	(0.023)	(0.024)	(0.030)	(0.017)	(0.019)	(0.026)	(0.020)	(0.022)	(0.028)
Younger than 10	0.364***			0.498***			0.570***		
	(0.088)			(0.099)			(0.136)		
Younger than 12		0.274***			0.413***			0.473***	
		(0.082)			(0.095)			(0.118)	
Younger than 15			0.291***			0.433***			0.582***
			(0.083)			(0.092)			(0.096)
Male	0.199***	0.190***	0.189***	0.199***	0.189***	0.186***	0.175**	0.168**	0.168**
	(0.069)	(0.069)	(0.070)	(0.068)	(0.068)	(0.069)	(0.068)	(0.069)	(0.068)
SES	−0.135*	−0.131*	−0.124*	−0.222***	−0.222***	−0.213***	−0.141**	−0.140**	−0.132*
	(0.072)	(0.072)	(0.072)	(0.070)	(0.070)	(0.070)	(0.071)	(0.071)	(0.071)
Edu	−0.050**	−0.055***	−0.057***	−0.013	−0.017	−0.020	−0.046**	−0.050**	−0.053***
	(0.021)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Mean Conf*Younger 10	−0.090***			−0.076**			−0.059*		
	(0.033)			(0.032)			(0.032)		
Mean Conf*Younger 12		−0.048			−0.055*			−0.024	
		(0.030)			(0.029)			(0.029)	
Mean Conf*Younger 15			−0.049			−0.044			−0.057*
			(0.031)			(0.031)			(0.031)
Constant	4.651***	4.668***	4.603***	4.094***	4.089***	3.998***	3.962***	3.941***	3.789***
	(0.161)	(0.161)	(0.166)	(0.155)	(0.157)	(0.162)	(0.164)	(0.166)	(0.166)
Mun. RE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age RE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,402	2,402	2,402	2,406	2,406	2,406	2,410	2,410	2,410
Log Likelihood	−4,668.314	−4,671.529	−4,671.112	−4,641.268	−4,643.137	−4,642.393	−4,655.895	−4,657.155	−4,652.576
Akaike Inf. Crit.	9,356.627	9,363.058	9,362.225	9,302.537	9,306.273	9,304.786	9,331.789	9,334.310	9,325.151
Bayesian Inf. Crit.	9,414.468	9,420.898	9,420.065	9,360.394	9,364.130	9,362.643	9,389.663	9,392.183	9,383.025
Note:									*p<0.1; **p<0.05; ***p<0.01

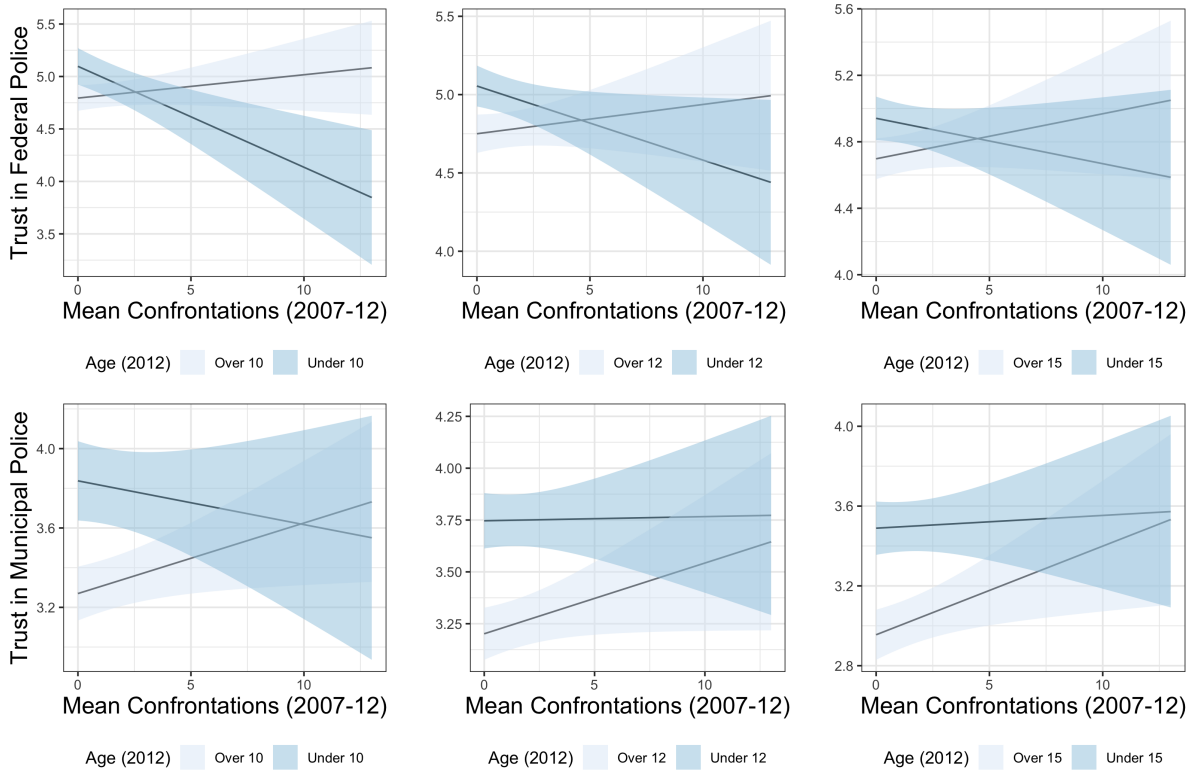
Table A21: Exposure to military confrontations and trust in military

	Dependent variable:					
	Army			Navy		
	(1)	(2)	(3)	(4)	(5)	(6)
Mean Confrontations	0.034*	0.040*	0.046*	0.036*	0.034	0.055**
	(0.019)	(0.021)	(0.027)	(0.019)	(0.021)	(0.026)
Younger than 10	0.306***			0.254***		
	(0.094)			(0.096)		
Younger than 12		0.316***			0.200**	
		(0.075)			(0.086)	
Younger than 15			0.271***			0.265***
			(0.080)			(0.081)
Male	0.263***	0.255***	0.257***	0.345***	0.341***	0.340***
	(0.065)	(0.065)	(0.065)	(0.064)	(0.064)	(0.064)
SES	−0.193***	−0.197***	−0.186***	−0.180***	−0.179***	−0.178***
	(0.067)	(0.067)	(0.067)	(0.066)	(0.066)	(0.066)
Edu	−0.028	−0.029	−0.032*	−0.019	−0.021	−0.021
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Mean Conf*Younger 10	−0.083***			−0.056*		
	(0.031)			(0.030)		
Mean Conf*Younger 12		−0.067**			−0.029	
		(0.028)			(0.027)	
Mean Conf*Younger 15			−0.053*			−0.051*
			(0.030)			(0.029)
Constant	5.522***	5.491***	5.456***	5.697***	5.699***	5.615***
	(0.151)	(0.149)	(0.155)	(0.148)	(0.149)	(0.153)
Mun. RE	Yes	Yes	Yes	Yes	Yes	Yes
Age RE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,408	2,408	2,408	2,394	2,394	2,394
Log Likelihood	−4,530.018	−4,528.717	−4,531.422	−4,451.570	−4,452.944	−4,450.713
Akaike Inf. Crit.	9,080.036	9,077.434	9,082.843	8,923.141	8,925.887	8,921.427
Bayesian Inf. Crit.	9,137.901	9,135.300	9,140.709	8,980.948	8,983.695	8,979.234
Note:						*p<0.1; **p<0.05; ***p<0.01

F5 Figures: exposure to militarization across age groups

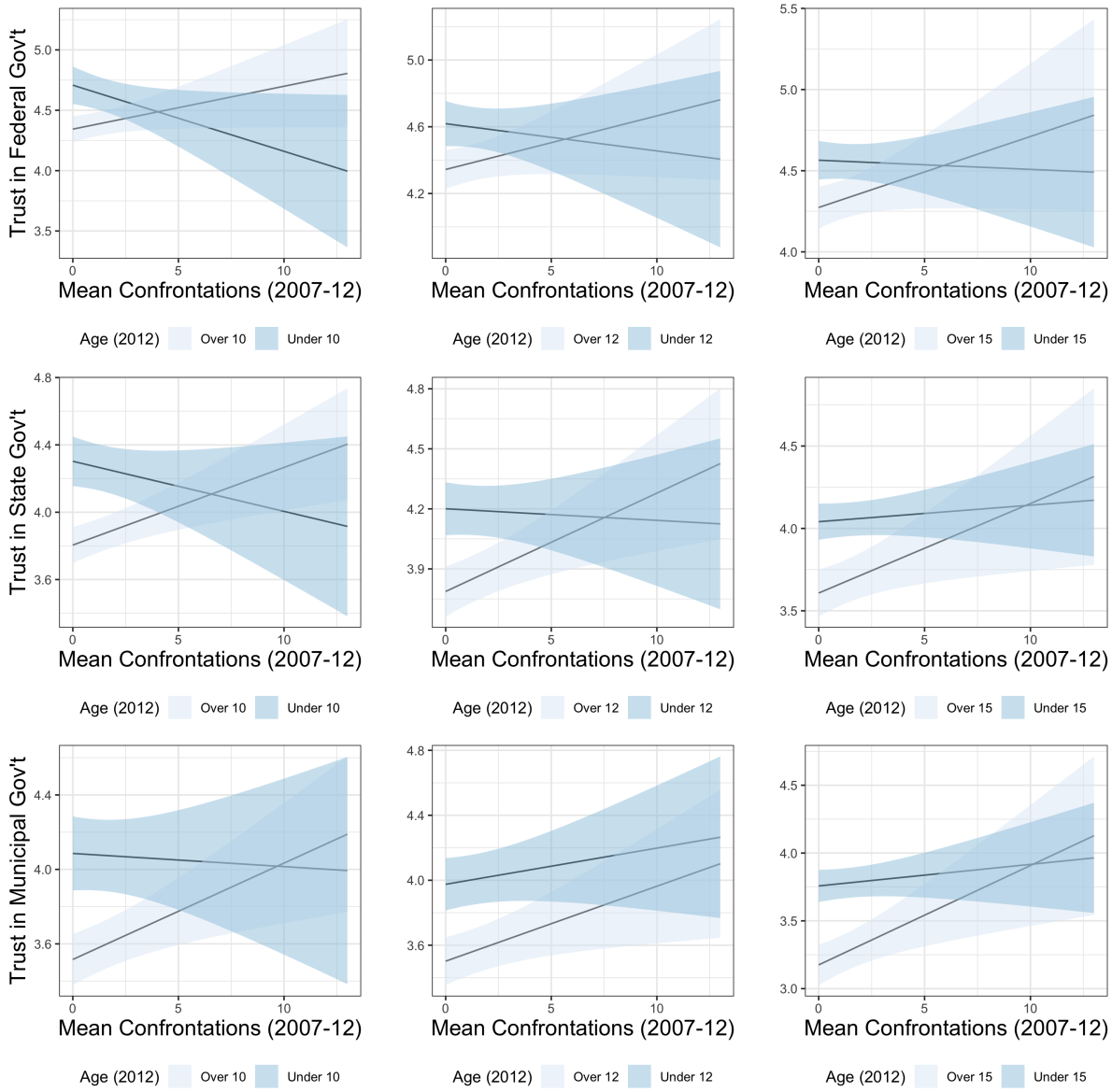
Additional figures regarding militarization for all age cut-offs explored are provided here.

Figure A5: Predicted values trust in police vs. mean municipal military confrontations (2007–12) by age group



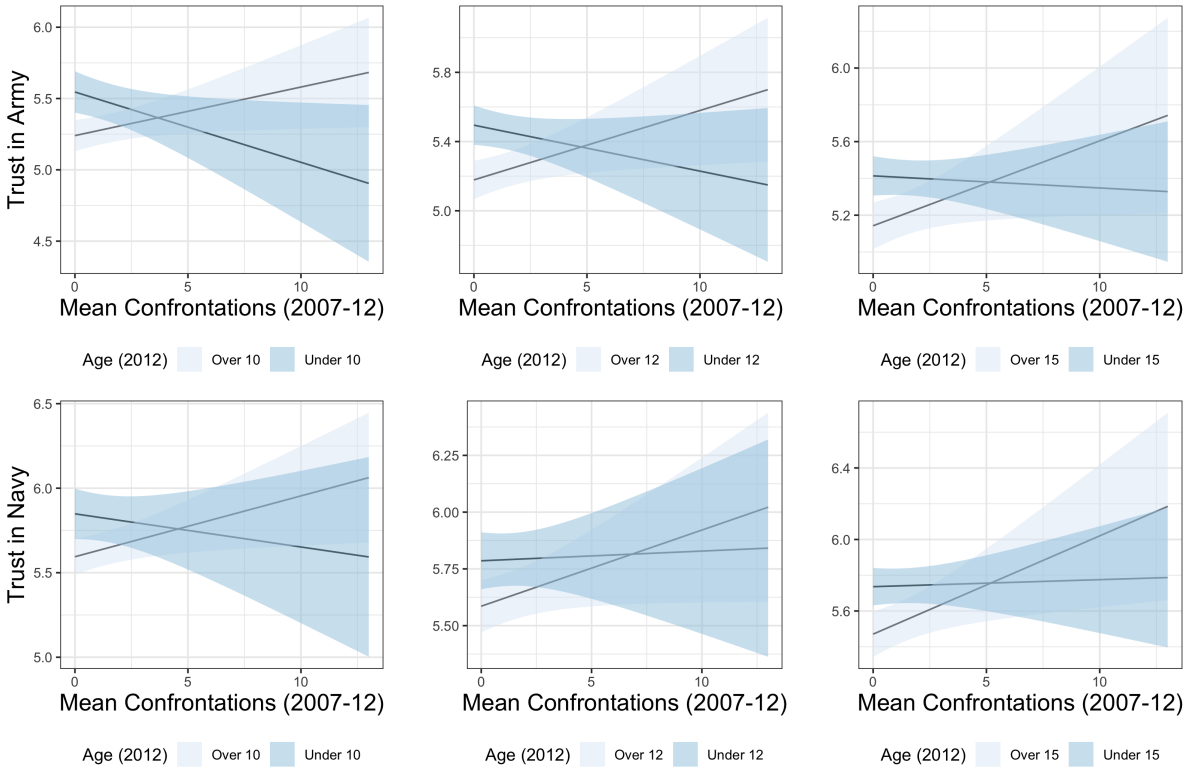
Note: trust is reported on a 1–7 scale. Mean confrontations are calculated as the average number of confrontations between the military and organized crime which each respondent was exposed to (based on their municipality of residence and birth year) for the years 2007–12. Figures present predicted values for each age group from random-intercept models with 90% semi-parametric bootstrapped confidence intervals.

Figure A6: Predicted values trust in government vs. mean municipal military confrontations (2007–12) by age group



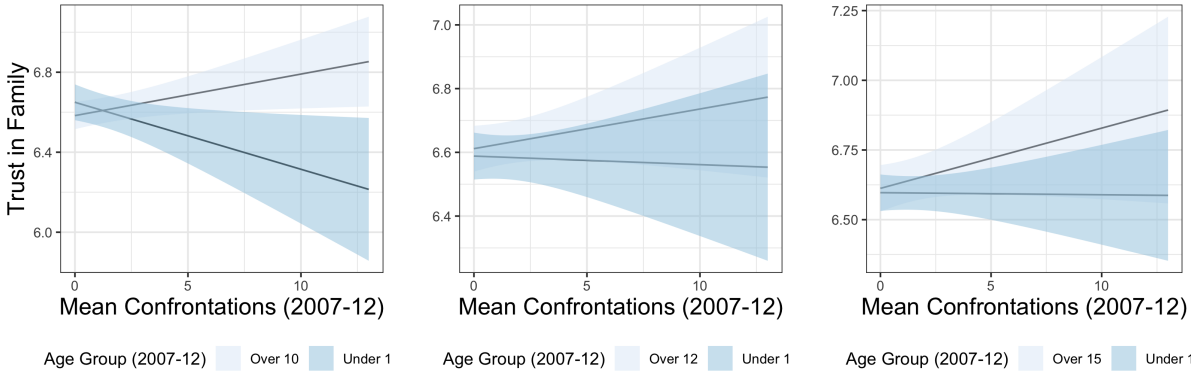
Note: trust is reported on a 1–7 scale. Mean confrontations are calculated as the average number of confrontations between the military and organized crime which each respondent was exposed to (based on their municipality of residence and birth year) for the years 2007–12. Figures present predicted values for each age group from random-intercept models with 90% semi-parametric bootstrapped confidence intervals.

Figure A7: Predicted values trust in military vs. mean municipal military confrontations (2007–12) by age group



Note: trust is reported on a 1–7 scale. Mean confrontations are calculated as the average number of confrontations between the military and organized crime which each respondent was exposed to (based on their municipality of residence and birth year) for the years 2007–12. Figures present predicted values for each age group from random-intercept models with 90% semi-parametric bootstrapped confidence intervals.

Figure A8: Predicted values of interpersonal trust vs. mean municipal military confrontations (2007–12) by age group



Note: trust is reported on a 1–7 scale. Mean confrontations are calculated as the average number of confrontations between the military and organized crime which each respondent was exposed to (based on their municipality of residence and birth year) for the years 2007–12. Figures present predicted values for each age group from random-intercept models with 90% semi-parametric bootstrapped confidence intervals.

F6 Exposure to militarization: two-way fixed effects models

Below are results from an alternative model specification, using two-way fixed effects for both municipality and birth year of respondents. Results are directionally consistent with our main results.

Table A22: Exposure to military confrontations and trust in fed police

	Dependent variable:		
	(1)	(2)	(3)
Mean confrontations	−1.418	−1.400	−1.337
	(2.189)	(2.193)	(2.195)
Younger than 10	0.495***		
	(0.174)		
Younger than 12		0.440**	
		(0.173)	
Younger than 15			0.425**
			(0.174)
Male	0.078	0.074	0.075
	(0.070)	(0.070)	(0.070)
SES	−0.169**	−0.166**	−0.167**
	(0.074)	(0.074)	(0.074)
Edu	−0.065***	−0.066***	−0.065***
	(0.021)	(0.021)	(0.021)
Mean conf*younger 10	−0.118***		
	(0.033)		
Mean conf*younger 12		−0.066**	
		(0.029)	
Mean conf*younger 15			−0.049
			(0.031)
Constant	5.359***	5.377***	5.361***
	(0.342)	(0.342)	(0.344)
Mun. FE	Yes	Yes	Yes
Age FE	Yes	Yes	
Observations	2,405	2,405	2,405
R^2	0.094	0.090	0.089
Adjusted R^2	0.046	0.043	0.042
Residual std. error (df = 2284)	1.643	1.646	1.647
F statistic (df = 120; 2284)	1.964***	1.894***	1.871***
Note:		*p<0.1; **p<0.05; ***p<0.01	

Table A23: Exposure to military confrontations and trust in mun. police

	Dependent variable:		
	(1)	(2)	(3)
Mean confrontations	−3.015	−3.006	−2.953
	(2.178)	(2.179)	(2.179)
Younger than 10	0.871***		
	(0.173)		
Younger than 12		0.843***	
		(0.173)	
Younger than 15			0.853***
			(0.173)
Male	0.076	0.075	0.076
	(0.069)	(0.070)	(0.070)
SES	−0.115	−0.113	−0.115
	(0.074)	(0.074)	(0.074)
Edu	−0.012	−0.013	−0.012
	(0.021)	(0.021)	(0.021)
Mean conf*younger 10	−0.056*		
	(0.032)		
Mean conf*younger 12		−0.029	
		(0.029)	
Mean conf*younger 15			−0.036
			(0.031)
Constant	3.391***	3.400***	3.379***
	(0.340)	(0.340)	(0.341)
Mun. FE	Yes	Yes	Yes
Age FE	Yes	Yes	
Observations	2,407	2,407	2,407
R^2	0.092	0.092	0.092
Adjusted R^2	0.045	0.044	0.044
Residual std. error (df = 2286)	1.635	1.636	1.636
F statistic (df = 120; 2286)	1.938***	1.920***	1.924***
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A24: Exposure to military confrontations and trust in state. police

	Dependent variable:		
	(1)	(2)	(3)
Mean confrontations	−1.276	−1.279	−1.213
	(2.180)	(2.180)	(2.180)
Younger than 10	0.645***		
	(0.173)		
Younger than 12		0.594***	
		(0.173)	
Younger than 15			0.650***
			(0.173)
Male	0.003	0.001	0.004
	(0.070)	(0.070)	(0.070)
SES	−0.114	−0.111	−0.115
	(0.074)	(0.074)	(0.074)
Edu	−0.027	−0.027	−0.026
	(0.021)	(0.021)	(0.021)
Mean conf*younger 10	−0.035		
	(0.032)		
Mean conf*younger 12		0.012	
		(0.029)	
Mean conf*younger 15			−0.037
			(0.031)
Constant	3.806***	3.826***	3.785***
	(0.341)	(0.341)	(0.342)
Mun. FE	Yes	Yes	Yes
Age FE	Yes	Yes	Yes
Observations	2,407	2,407	2,407
R^2	0.071	0.071	0.071
Adjusted R^2	0.023	0.022	0.023
Residual std. error (df = 2286)	1.636	1.637	1.636
F statistic (df = 120; 2286)	1.462***	1.453***	1.464***
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A25: Exposure to military confrontations and trust in family

	Dependent variable:		
	(1)	(2)	(3)
Mean confrontations	0.096	0.100	0.130
	(1.362)	(1.363)	(1.364)
Younger than 10	−0.009		
	(0.108)		
Younger than 12		−0.051	
		(0.108)	
Younger than 15			−0.041
			(0.108)
Male	0.097**	0.095**	0.096**
	(0.043)	(0.043)	(0.043)
SES	0.131***	0.133***	0.132***
	(0.046)	(0.046)	(0.046)
Edu	0.035***	0.035***	0.035***
	(0.013)	(0.013)	(0.013)
Mean conf*younger 10	−0.052**		
	(0.020)		
Mean conf*younger 12		−0.012	
		(0.018)	
Mean conf*younger 15			−0.020
			(0.019)
Constant	6.341***	6.356***	6.343***
	(0.213)	(0.213)	(0.214)
Mun. FE	Yes	Yes	Yes
Age FE	Yes	Yes	Yes
Observations	2,410	2,410	2,410
R^2	0.069	0.067	0.067
Adjusted R^2	0.020	0.018	0.018
Residual std. error (df = 2289)	1.022	1.023	1.023
F statistic (df = 120; 2289)	1.415***	1.361***	1.367***
Note:		*p<0.1; **p<0.05; ***p<0.01	

Table A26: Exposure to military confrontations and trust in neighbours

	Dependent variable:		
	(1)	(2)	(3)
Mean confrontations	−0.078	−0.071	−0.060
	(2.433)	(2.433)	(2.434)
Younger than 10	−0.268		
	(0.193)		
Younger than 12		−0.274	
		(0.192)	
Younger than 15			−0.289
			(0.193)
Male	0.323***	0.323***	0.323***
	(0.078)	(0.078)	(0.078)
SES	0.097	0.097	0.098
	(0.082)	(0.082)	(0.082)
Edu	0.111***	0.111***	0.111***
	(0.023)	(0.023)	(0.023)
Mean conf*younger 10	−0.032		
	(0.036)		
Mean conf*younger 12		−0.025	
		(0.032)	
Constant			−0.011
			(0.035)
Constant	3.071***	3.073***	3.074***
	(0.380)	(0.380)	(0.381)
Mun. FE	Yes	Yes	Yes
Age FE	Yes	Yes	Yes
Observations	2,407	2,407	2,407
R^2	0.094	0.094	0.094
Adjusted R^2	0.047	0.047	0.047
Residual std. error (df = 2286)	1.826	1.827	1.827
F statistic (df = 120; 2286)	1.984***	1.983***	1.978***
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A27: Exposure to military confrontations and trust in fed gov't

	Dependent variable:		
	(1)	(2)	(3)
Mean confrontations	2.064	2.076	2.144
	(2.217)	(2.219)	(2.220)
Younger than 10	0.403**		
	(0.176)		
Younger than 12		0.357**	
		(0.176)	
Younger than 15			0.360**
			(0.176)
Male	0.190***	0.187***	0.188***
	(0.071)	(0.071)	(0.071)
SES	−0.096	−0.093	−0.094
	(0.075)	(0.075)	(0.075)
Edu	−0.054**	−0.055**	−0.054**
	(0.021)	(0.021)	(0.021)
Mean conf*younger 10	−0.091***		
	(0.034)		
Mean conf*younger 12		−0.048	
		(0.030)	
Mean conf*younger 15			−0.048
			(0.032)
Constant	4.040***	4.055***	4.031***
	(0.346)	(0.346)	(0.347)
Mun. FE	Yes	Yes	Yes
Age FE	Yes	Yes	Yes
Observations	2,402	2,402	2,402
R^2	0.091	0.089	0.089
Adjusted R^2	0.043	0.041	0.041
Residual std. error (df = 2281)	1.664	1.666	1.666
F statistic (df = 120; 2281)	1.895***	1.851***	1.848***
Note:		*p<0.1; **p<0.05; ***p<0.01	

Table A28: Exposure to military confrontations and trust in state gov't

	Dependent variable:		
	(1)	(2)	(3)
Mean confrontations	−1.662	−1.650	−1.597
	(2.201)	(2.202)	(2.203)
Younger than 10	0.766***		
	(0.175)		
Younger than 12		0.748***	
		(0.174)	
Younger than 15			0.743***
			(0.175)
Male	0.175**	0.174**	0.175**
	(0.070)	(0.070)	(0.070)
SES	−0.210***	−0.209***	−0.210***
	(0.074)	(0.074)	(0.074)
Edu	−0.019	−0.019	−0.018
	(0.021)	(0.021)	(0.021)
Mean conf*younger 10	−0.064*		
	(0.033)		
Mean conf*younger 12		−0.046	
		(0.029)	
Mean conf*younger 15			−0.039
			(0.031)
Constant	3.988***	3.993***	3.978***
	(0.344)	(0.344)	(0.345)
Mun. FE	Yes	Yes	Yes
Age FE	Yes	Yes	Yes
Observations	2,406	2,406	2,406
R^2	0.076	0.076	0.075
Adjusted R^2	0.028	0.027	0.027
Residual std. error (df = 2285)	1.653	1.653	1.653
F statistic (df = 120; 2285)	1.572***	1.560***	1.552***
Note:		*p<0.1; **p<0.05; ***p<0.01	

Table A29: Exposure to military confrontations and trust in mun gov't

	Dependent variable:		
	(1)	(2)	(3)
Mean confrontations	−0.603	−0.596	−0.510
	(2.196)	(2.197)	(2.197)
Younger than 10	1.006***		
	(0.174)		
Younger than 12		0.971***	
		(0.174)	
Younger than 15			1.008***
			(0.175)
Male	0.167**	0.165**	0.168**
	(0.070)	(0.070)	(0.070)
SES	−0.181**	−0.180**	−0.183**
	(0.074)	(0.074)	(0.074)
Edu	−0.053**	−0.053**	−0.052**
	(0.021)	(0.021)	(0.021)
Mean conf*younger 10	−0.057*		
	(0.033)		
Mean conf*younger 12		−0.023	
		(0.029)	
Mean conf*younger 15			−0.055*
			(0.031)
Constant	3.362***	3.375***	3.334***
	(0.343)	(0.343)	(0.344)
Mun. FE	Yes	Yes	Yes
Age FE	Yes	Yes	Yes
Observations	2,410	2,410	2,410
R^2	0.097	0.096	0.097
Adjusted R^2	0.050	0.049	0.050
Residual std. error (df = 2289)	1.649	1.650	1.649
F statistic (df = 120; 2289)	2.059***	2.037***	2.060***
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A30: Exposure to military confrontations and trust in army

	Dependent variable:		
	(1)	(2)	(3)
Mean confrontations	−0.419	−0.400	−0.335
	(2.091)	(2.091)	(2.093)
Younger than 10	0.272		
	(0.166)		
Younger than 12		0.258	
		(0.165)	
Younger than 15			0.244
			(0.166)
Male	0.261***	0.260***	0.261***
	(0.067)	(0.067)	(0.067)
SES	−0.193***	−0.193***	−0.193***
	(0.071)	(0.071)	(0.071)
Edu	−0.022	−0.022	−0.021
	(0.020)	(0.020)	(0.020)
Mean conf*younger 10	−0.082***		
	(0.031)		
Mean conf*younger 12		−0.067**	
		(0.028)	
Mean conf*younger 15			−0.052*
			(0.030)
Constant	5.574***	5.576***	5.560***
	(0.326)	(0.326)	(0.328)
Mun. FE	Yes	Yes	Yes
Age FE	Yes	Yes	Yes
Observations	2,408	2,408	2,408
R^2	0.081	0.080	0.079
Adjusted R^2	0.033	0.032	0.031
Residual std. error (df = 2287)	1.569	1.570	1.571
F statistic (df = 120; 2287)	1.675***	1.665***	1.640***
Note:		*p<0.1; **p<0.05; ***p<0.01	

Table A31: Exposure to military confrontations and trust in navy

	Dependent variable:		
	(1)	(2)	(3)
Mean confrontations	−1.982	−1.975	−1.899
	(2.046)	(2.047)	(2.047)
Younger than 10	0.253		
	(0.163)		
Younger than 12		0.225	
		(0.162)	
Younger than 15			0.253
			(0.163)
Male	0.343***	0.342***	0.344***
	(0.066)	(0.066)	(0.066)
SES	−0.146**	−0.145**	−0.147**
	(0.069)	(0.069)	(0.069)
Edu	−0.020	−0.020	−0.019
	(0.020)	(0.020)	(0.020)
Mean conf*younger 10	−0.052*		
	(0.031)		
Mean conf*younger 12		−0.026	
		(0.027)	
Mean conf*younger 15			−0.049*
			(0.029)
Constant	5.873***	5.882***	5.847***
	(0.320)	(0.320)	(0.321)
Mun. FE	Yes	Yes	Yes
Age FE	Yes	Yes	Yes
Observations	2,394	2,394	2,394
R^2	0.083	0.083	0.083
Adjusted R^2	0.035	0.034	0.035
Residual std. error (df = 2273)	1.536	1.537	1.536
F statistic (df = 120; 2273)	1.722***	1.703***	1.721***
Note:			*p<0.1; **p<0.05; ***p<0.01

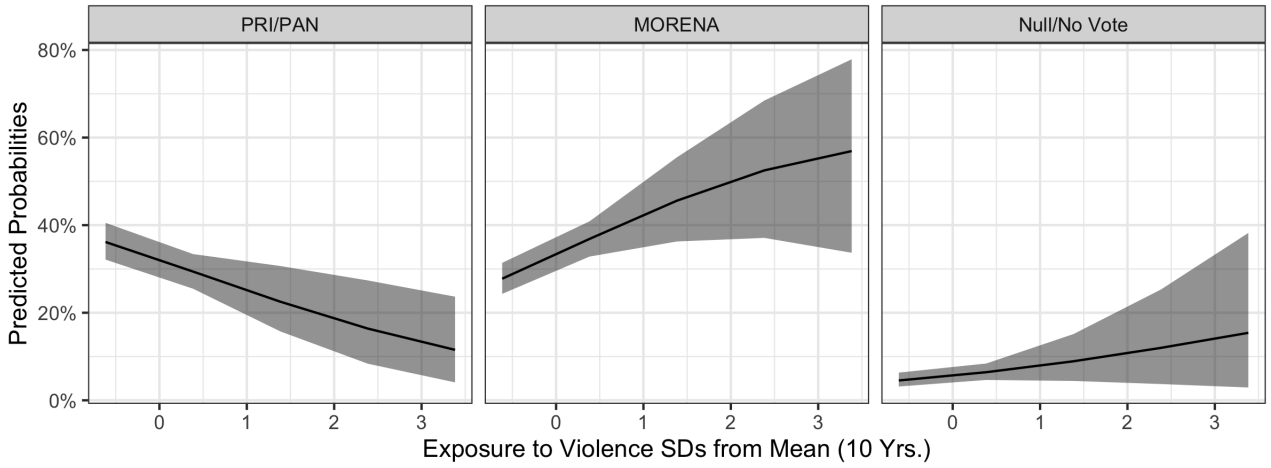
G Party choice

In this section, we present an exploratory analysis assessing the link between exposure to violence during childhood and vote choice later in life. Table A32 presents results from multinomial logistic regressions examining the impact of violence exposure during respondents' youth on their party choice for the 2021 Chamber of Deputies election. Figure A9 shows the predicted probability of vote choice for our statistically significant results. We expect exposure to violence to increase respondents' probability to vote for parties other than the PRI and PAN (specified as the reference category in the model). We find support for this hypothesis. Specifically, we find that increased exposure to violence for the first ten years of life leads to an increased probability that the respondent voted for MORENA or chose not to vote/submitted a null vote. In particular, a one standard deviation increase in the average homicide rate during one's first ten years of life results in respondents being 1.74 times more likely to vote for MORENA vs. the PAN or PRI and similarly 1.74 times more likely to submit a null vote or not vote at all vs. voting for the PAN or PRI.[2] Exposure to violence does not result in an increased probability of voting for the PRD or other smaller parties in either time period.

Table A32: Party choice in 2021 Chamber of Deputies election

	Dependent variable:			
	MORENA	Null/No vote	Other	PRD
	(1)	(2)	(3)	(4)
Expos. 10 yrs	0.553^{***}	0.556^{*}	0.077	0.073
	(0.199)	(0.310)	(0.227)	(0.527)
Male	0.559^{***}	0.784^{**}	0.219	0.169
	(0.184)	(0.351)	(0.193)	(0.462)
SES	−0.148	−0.009	0.251	−0.218
	(0.199)	(0.388)	(0.219)	(0.475)
Edu	−0.053	0.050	−0.063	−0.090
	(0.054)	(0.106)	(0.057)	(0.132)
Constant	0.376	-1.970^{**}	−0.585	−1.112
	(0.496)	(0.929)	(0.545)	(1.134)
Akaike inf. crit.	2,145.760	2,145.760	2,145.760	2,145.760
Note:				*p<0.1; **p<0.05; ***p<0.01

Figure A9: Predicted probs of vote choice in 2021 Chamber of Deputies election (90% simulated CIs)



[2] These values represent odds ratios and are calculated by computing the exp of of the appropriate coefficient.

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