Report on Police Professionalization and Citizen Trust

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Introduction

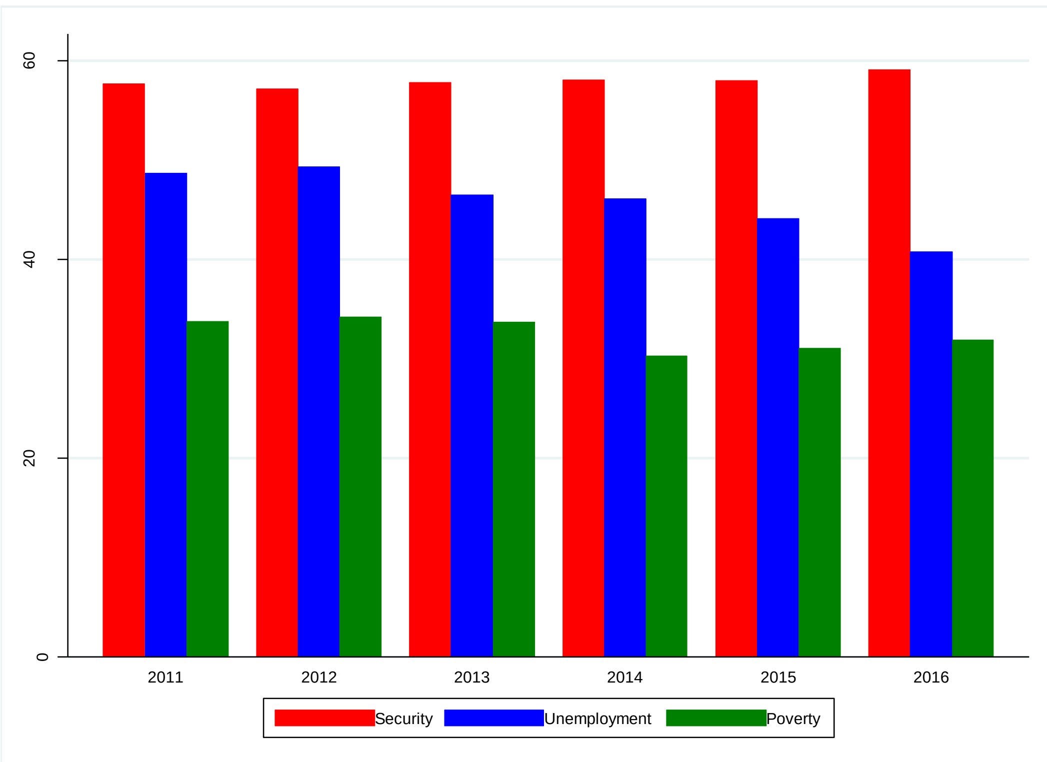
Achieving cooperation between the public and police is a necessary condition for effective law enforcement. Lack of police legitimacy is a serious problem for any society's capacity to control crime, and a consensus is emerging among crime experts that police legitimacy is an end in itself. Police legitimacy derives from police behavior. When officers adhere to rules, maintain their neutrality, and treat citizens with respect, their legitimacy and effectiveness increases. Conversely, when residents believe the police are untrustworthy or corrupt, they are less likely to report crimes or aid their investigation. Thereby preventing even good police officers from being able to do their jobs.

This report analyzes the National Survey of Victimization and Perception of Public Security (ENVIPE) to further the understanding of the dynamics of police legitimacy. Since 2011, this survey has been collected annually by the Mexican Institute of Statistics and Geography (INEGI) with the goal of providing information on self-reported victimization, perceptions of public safety and police performance, and the social and economic context of crime. The report is divided into three parts. The first focuses on the national and state context of crime over time and its impact on individual experiences and attitudes towards crime. Part two analyzes citizen satisfaction with police, with an emphasis on their perceptions of police ineffectiveness and corruption and distrust of local and federal levels of police. Finally, part three approaches police legitimacy and citizen cooperation with police by evaluating the impact of three policies related to police professionalization.

I. Citizen Security, Crime, and Perceptions of Police Performance

In order to understand the socioeconomic context of crime, we begin by analyzing the problems that Mexicans consider the most important issues faced by the country. ENVIPE asks respondents to select the three issues – from a list of 12 items in the 2016 edition – that worry them the most. Figure 1 shows the three issues that, at the national level, are considered the most important over the last six years. Security ranks in the first place with 60% of the population considering it the greatest problem. This trend has remained steady over time, with a slight increase in concerns over security in 2016. In second and third place – with percentages below 50 – are unemployment and poverty, respectively. Worries over unemployment appear to have decreased over the last several years, however, the percentage of the population concerned about poverty has shown slight increases since 2014.

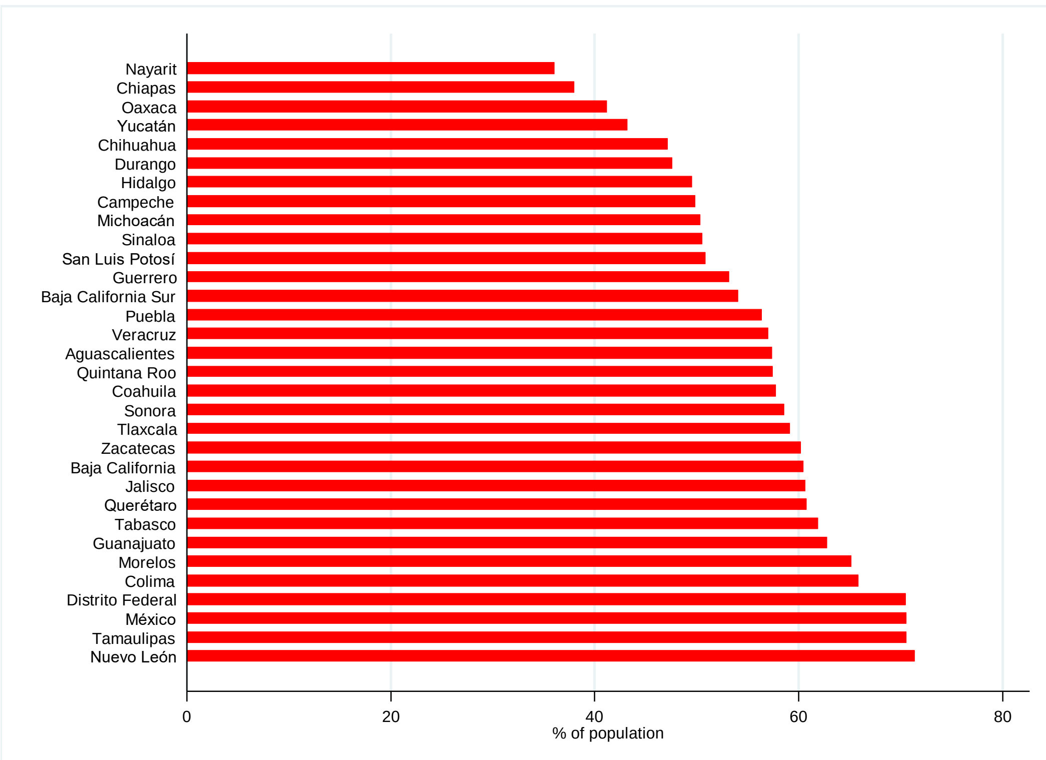
Figure 1. Most Critical Problem Facing the Country, % of population



Source: Stanford Poverty, Violence and Governance Lab with data from ENVIPE 2011-2016.

The national trend is not followed by all the states. For example, although the most recent edition of ENVIPE records the highest national percentage of people worried most about security, there were inter-state variations of up to 30 percentage points. Figure 2 shows that, in 2016, there was a group of states where more than 70% of the population was worried most by insecurity and another group where rates were below 50%, with the greatest concerns being health, unemployment, and poverty. As expected, the first group includes states that have suffered high rates of violent crime—in some cases related to Drug Trafficking Organizations (DTOs)—such as Nuevo Leon, Tamaulipas, Mexico State, and Distrito Federal. The second group, located at the opposite extreme of the distribution, includes states such Nayarit, Chiapas, Oaxaca, and Yucatan that are generally considered less violent than the rest of the country.

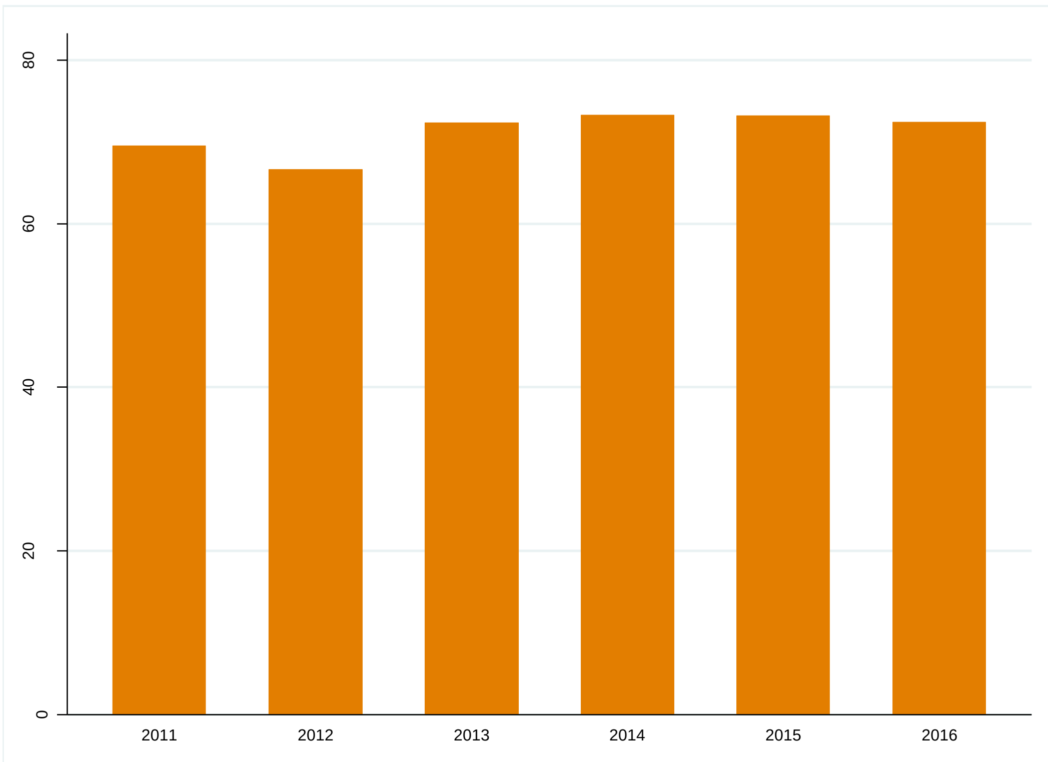
Figure 2. Security as the Most Important Problem by State, 2016



Source: Stanford Poverty, Violence and Governance Lab with data from ENVIPE 2011-2016.

After further comparison, concerns over security appear to relate to the probability of feeling unsafe in one’s state. Figure 3 compares the percentage of people, nation-wide, who considered themselves insecure in their state between 2011 and 2016. Similar to the analysis of citizens' greatest concerns, there is no large variation across time in the perception of insecurity in one's state. However, a greater percentage of respondents reported feeling unsafe in their state, as compared to the percentage who responded that security was one of the country's largest issues. While approximately 60% of Mexicans consider security a major concern, almost 70% report feeling insecure in their state.

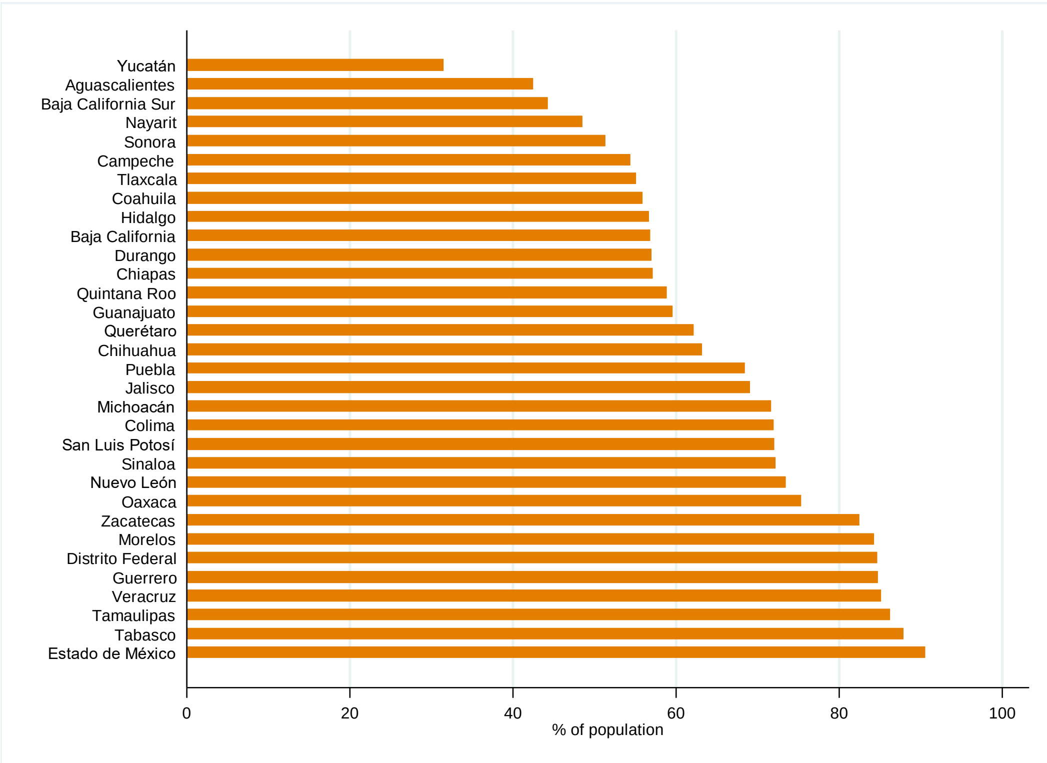
Figure 3. Perception of Insecurity over Time, % of population



Source: Stanford Poverty, Violence and Governance Lab with data from ENVIPE 2011-2016.

Beyond the national numbers, there is considerable variation at the state level. As shown in Figure 4, variation across states in the perception of insecurity is even greater than the previously discussed variability for perception of the most important problem, reaching differences of up to 60 percentage points. In the lowest-ranked state, Yucatan, around 30% of respondents feel insecure. While in Mexico State, 90% of respondents feel insecure. Interestingly, roughly 70% of respondents in Nuevo Leon feel insecure and consider security the most important problem, however, the state is not among the most insecure states. Again, ENVIPE shows that there is a group of states that appears to be perceived as less violent than the average and another group of states with the opposite perception.

Figure 4. Perception of Insecurity by State, 2016

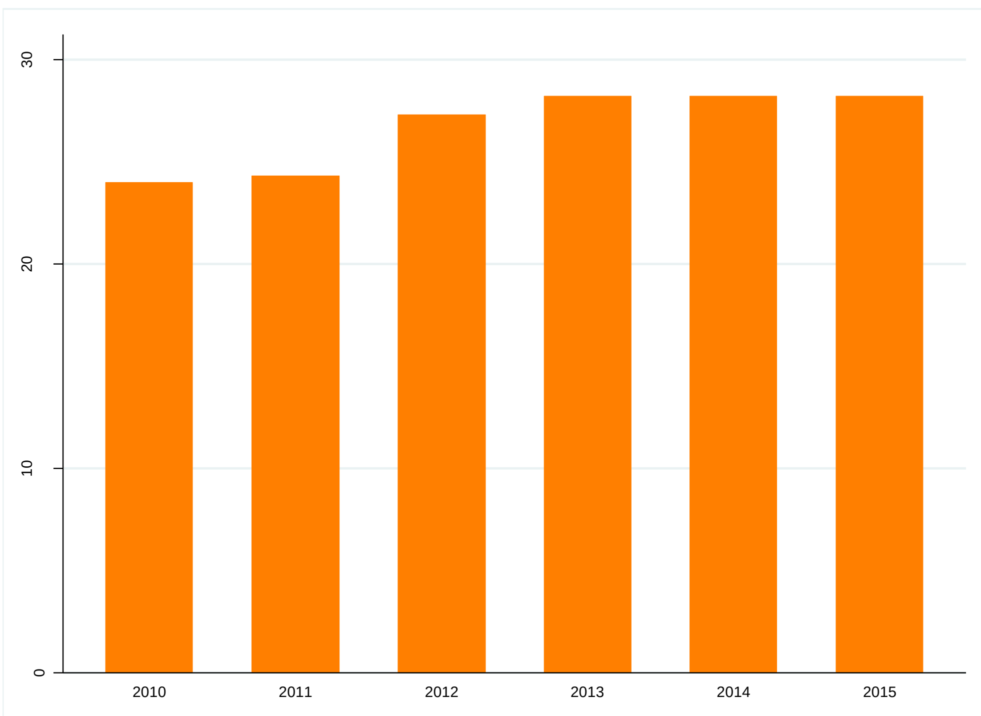


Source: Stanford Poverty, Violence and Governance Lab with data from ENVIPE 2011-2016.

Together, the questions regarding Mexicans' greatest worries and those concerning feelings of insecurity in their state suggest that crime and violence are considered important problems at the national level and in certain states. These insights raise additional questions about the relationship between the perception of insecurity and actual victimization and crime. Is this perception of insecurity correlating with the probability of being the victim of a crime? Do states with the highest perceptions of insecurity also experience the highest victimization rates? In other words, are perceptions of insecurity motivated by fear of crime? The following graph shows the percentage of people who report experiencing a crime of any kind from 2010-2015.[1] However, it is important to recall that ENVIPE is a survey based on individual perceptions. Victimization rates are based on self-reported experiences, which could differ from official crime rates.[2]

Figure 5 presents that about 25% of the population was the victim of some crime in 2010 and this parentage has increased over time. In addition, the figure shows that the relative number of victims rapidly increased after 2011. The data shown in the figure is corroborated by the similar self-reported victimization rates presented in international surveys like LAPOP. In fact, if we compare ENVIPE's victimization rate with LAPOP's estimations for other Latin-American countries, Mexico's crime rate is at least 5 percentage points above the regional average and just below those of Peru and Ecuador (LAPOP, 2015).

Figure 5. Crime Victimization over Time, % of population



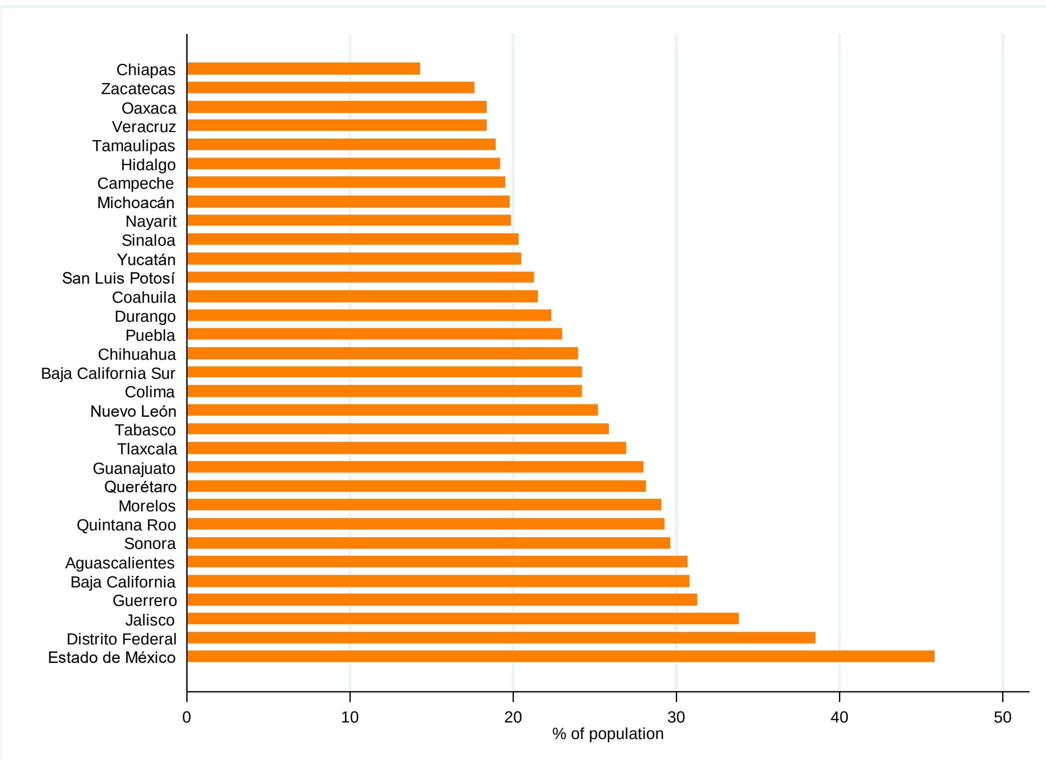
Source: Stanford Poverty, Violence and Governance Lab with data from ENVIPE 2011-2016.

[1] For self-reported victimization, ENVIPE collects information on the immediately previous year – i.e. if the survey was collected in 2011, questions on victimization are specifically referring to 2010 victimization experiences.

[2] ENVIPE is only representative of individuals over the age of 18.

With these data in mind, one could argue that Mexico's high victimization rate could possibly explain why more than 70% of the population perceives their state to be unsafe. Nevertheless, at the state level, Figure 6 shows that victimization, in 2015, like perceptions of insecurity, varied considerably across states. While at the national level, and in the majority of states, one in four citizens has been a victim of a crime. This percentage increases for states like Jalisco, Distrito Federal, and Mexico State where the rate is above 30%. In Mexico State, the state with the highest victimization rate, more than 45% of the citizens reported having been the victim of a crime. In the least victimized states, Chiapas, Zacatecas, Oaxaca, Veracruz, Tamaulipas, Hidalgo, Campeche, Michoacan, and Nayarit rates are below 20%.

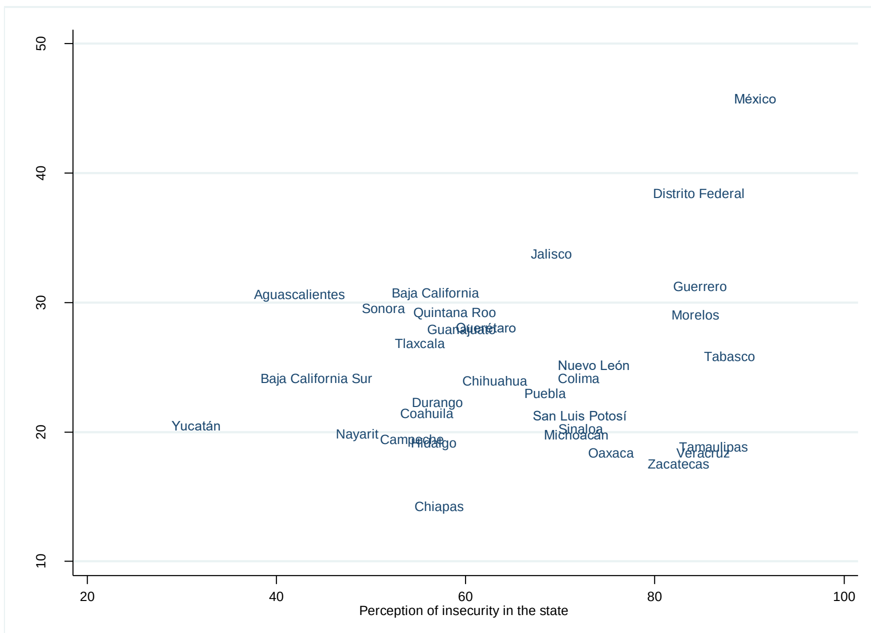
Figure 6. Crime Victimization by State, 2015



Source: Stanford Poverty, Violence and Governance Lab with data from ENVIPE 2011-2016.

Unlike perceptions of insecurity, the highest victimization rates are present in three states with large urban populations that are not clearly linked to DTOs' violence. Furthermore, the highest and lowest victimization rates do not necessarily correspond with the highest and lowest rates of feeling unsafe. In Figure 7, we compare the rates of victimization and feelings of insecurity from the most recent edition of ENVIPE. Although it appears that the correlation is positive, with Mexico State in one extreme and Yucatan in the other, there are states where it is not clear if victimization rates could explain the feeling of not being secure in the state. Some of the most interesting examples are Veracruz and Tamaulipas where the reported victimization rate is below 20%, yet more than 80% of their population feel insecure.

Figure 7. Perception of Insecurity and Crime Victimization by State, 2016



Source: Stanford Poverty, Violence and Governance Lab with data from ENVIPE 2011-2016.

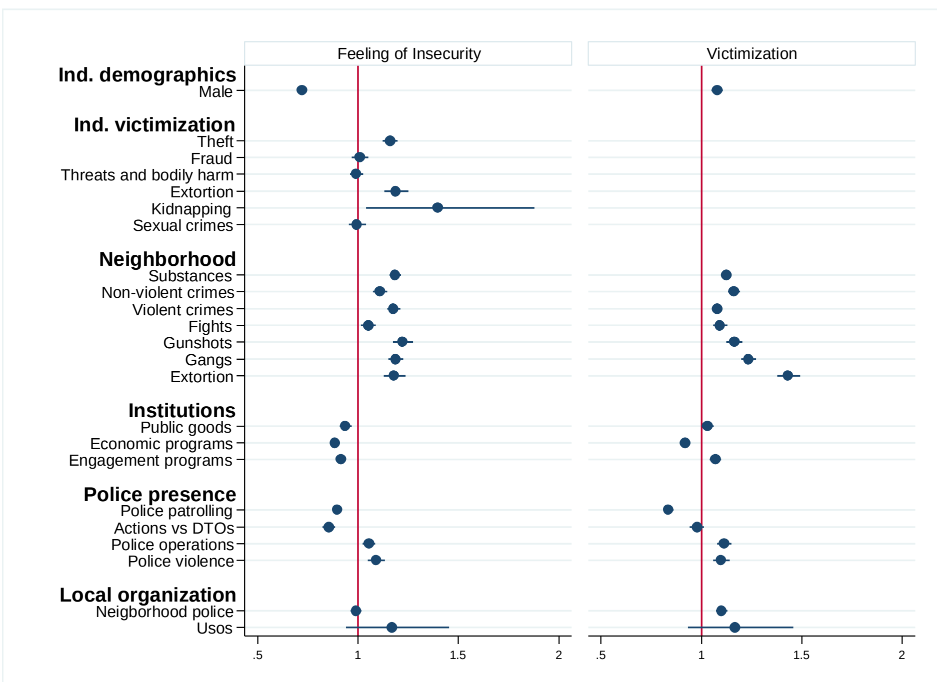
How do victimization rates relate to the feeling of insecurity?

The previous figures suggest that there is a correlation between urban settings and high crime rates and that these rates could be possibly correlated with perceptions of insecurity. However, it is not clear if this correlation is valid for every state and there are unanswered questions that remain. Specifically, why can states with similar victimization rates drastically differ in perceptions of insecurity? Are some crimes more effective than others in diminishing perceptions of security? Which individual and neighborhood characteristics increase the likelihood of suffering a crime?

Based on the individual-level information of ENVIPE and using information from 2011 to 2016, we address these questions by running logistic regressions that stem from three hypotheses. First, individual specific characteristics – particularly, socioeconomic status – and victimization experiences can explain differences in crime perceptions across individuals. Second, individuals living in dangerous neighborhoods are more likely to feel insecure or report having been the victim of a crime – we believe that fear of crime is associated with violent settings. Third, state presence and police presence (public goods provision, police patrolling, and actions against DTOs) are effective at decreasing individual perceptions on security and crime.

Figure 8 displays the probability in which each variable correlates with the feeling of insecurity and self-reported victimization. The red line separates increases in the probabilities (right side) from decreases in the probabilities (left side). Confidence intervals are indicated with horizontal lines. When the interval touches the red line, it indicates that we cannot be certain that the covariate has a significant effect in municipal and state distrust.

Figure 8. Estimated Effect Sizes of Predictors of Feeling Insecure and Being Victim of a Crime



Note: Logit models with state and year FE and the interaction of both terms. 95% confidence intervals. Clustered standard errors by municipality. Observations weighted by survey weights. Models are also controlled for age, employment status, and family size. Further details of the estimation in the Appendix.

In the feeling of insecurity model (Figure 8), males have a lower probability of reporting to feel insecure than females. Additionally, individuals who were victims of theft, extortion, or kidnapping have a higher chance of feeling insecure. Victims of fraud, threats and bodily harm, or sexual crimes do not have significantly different perceptions of security than non-victims of those crimes.[3] In terms of the neighborhood features – which are characteristics that approximate the social deterioration of the neighborhood – the presence of each factor correlates positively with higher levels of perceived insecurity, with gunshots presenting the highest impact. This means that individuals who have heard shots fired in their neighborhood have a 22% higher chance of feeling insecure.

The model also shows that institutional development is important in the determination of individual perceptions of insecurity. When public goods and public programs are present in the neighborhood, individuals are less likely to perceive insecurity. This relationship also holds true with police patrolling and public actions against DTOs. However, individuals living in neighborhoods with police violence or where police operations have occurred are likely to report feeling insecure. Regarding local forms of organization and governance, whether if the community is governed under Usos y Costumbres or whether the neighbors have organized to create a local police (private or from the neighborhood), do not seem to increase or decrease the probability of feeling insecure.

Although males, on average, are less likely to feel insecure, the victimization model shows that they are more likely to suffer crimes than females. In addition – as shown in the appendix –, prior victimization increases the probability of suffering a crime in 300%. Regarding the impact of neighborhood quality on individual victimization, the effects are positive and significant. The highest coefficient is shown by extortion, which was expected, given that it is one of the most-reported crimes in the survey.

[3] For visualization purposes, the figure does not include the variable of having been victim of a crime in any year before the collection of the survey. Nevertheless, its impact is significant, but smaller than the rest of the victimization variables.

Similar to the model of feeling of insecurity, police patrolling is associated with decreases in the probability of experiencing a crime. In addition, individuals that observe police violence and police operations are, on average, more likely to report having suffered a crime. In terms of institutional presence and programs, it is interesting that, unlike the case of feeling of insecurity, public goods are positively associated with the probability of being victimized. "Public goods" is an index that includes the provision of courts and parks and public lighting. To understand this effect, we ran the model with both variables and found that the positive estimate is mainly driven by the courts and parks component. In fact, the provision of public lightning is associated with a decrease of 7% in the probability of being victimized. Positive correlation with victimization levels – like the effect of engagement programs – could be explained with them being implemented in the communities with the highest crime rates.

Both models were also controlled for socioeconomic background and state and year fixed effects.[4] Because our analysis is motivated by differences across individuals and states, we further the analysis by estimating the predicted probability of each socioeconomic group and state. ENVIPE does not include a measure of income, so we approximate the individuals' socioeconomic status by analyzing the interaction between their educational attainment and whether they live in an urban setting. Previous studies suggest that educational attainment and urban settings are important determinants of crime perceptions; specifically, both associate with increases in the probability of suffering a crime. However, our analysis suggests that these associations vary across socioeconomic groups.

Figure 9 predicts that individuals in rural localities have a higher probability of feeling insecure than those in urban settings, but they are also less likely to be victims of a crime than those from urban settings. The figure also shows there is no significant difference in the probabilities of feeling insecure between urban and rural individuals that have attained at least one year of preschool or primary education (or no education at all). However, as years of schooling increase,

[4] The models also include the interaction of both fixed effects, which allows us to control for state changes over time.

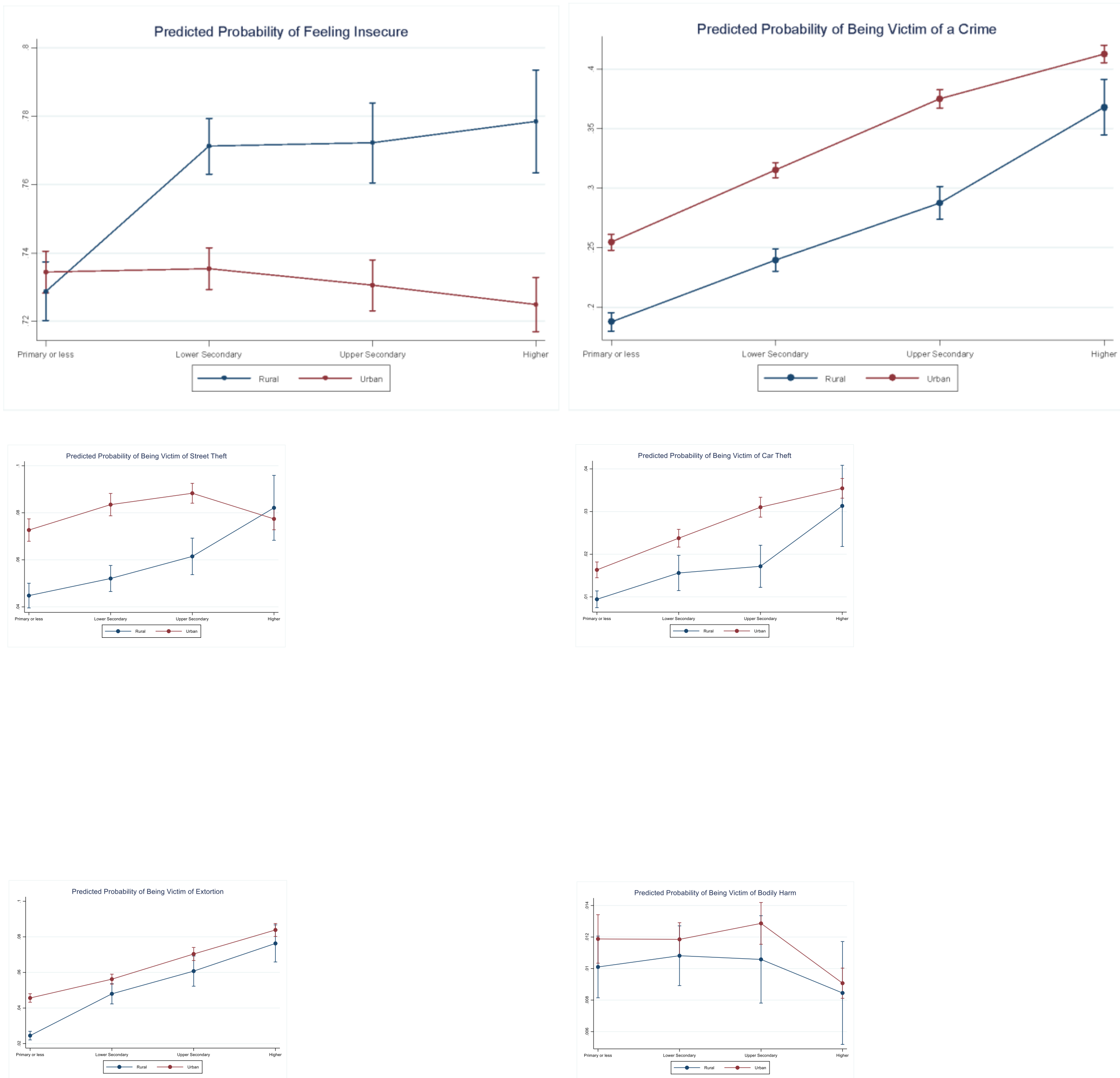
differences become significant with educated individuals living in rural communities being 5 percentage points more likely to feel insecure than educated individuals in urban settings.

In the case of general victimization, the figure shows that for both rural and urban individuals, years of schooling increase the probability of reporting being the victim of a crime, with highly educated individuals being 20 percentage points more likely than uneducated ones in both kinds of settings to suffer a crime. Furthermore, if we separately analyze the predicted probabilities of the most reported crimes in ENVIPE, we observe that the probability of urban individuals to suffer car or street theft is higher than the one of rural individuals at almost every level of education, except for higher education where differences are not significant. Nevertheless, both graphs show that the predicted probability of theft increases as years of education increase for both types of settings.

In terms of the predicted probability of suffering extortion, the figure suggests a clear trend in which the higher the level of education, the bigger the probability. In addition, when we compare types of settings, probabilities are only significantly different at the lowest level of education. For educated individuals, living in rural or urban municipalities does not affect the probability of being extorted. [5] Concerning the predicted probability of suffering bodily harm, the graph does not present significant differences between settings and years of schooling. This suggest that, regardless of the socioeconomic background of the individual, the probability of being bodily harmed is below 10%.

[5] As show in the Appendix (Table A2), another demographic factor that explains differences in the probability of being extorted is gender. While males hold higher probabilities of suffering crimes than females, in the case of extortion, females are in fact more vulnerable. It is important to clarify that the indicator of extortion in ENVIPE is mainly driven by phone extortion, which could explain why females are more likely to report being victims of it.

Figure 9. Predicted Probabilities of Feeling Insecure and Being Victim of a Crime by Socioeconomic Status



Predictive Margins with 95% confidence intervals. Further detailed in the Appendix.

The following maps show the change in the predicted probabilities for state and time variations from 2011 to 2016. In both cases, green states show decreases in the probability from 2011 to 2016 and states in red show the states in which an individual's probability of feeling insecure or suffering a crime increased. In both cases, the darkest colors demonstrate the greatest changes. On the one hand, the map in Figure 10 shows that the probability of feeling insecurity decreased in the majority of states from 2011 to 2016. In particular, states such as Durango, Chihuahua, Aguascalientes and Nuevo Leon seem to have considerably improved their citizen perception of insecurity. Nevertheless, in states like Baja California Sur, Guanajuato, Queretaro, Tlaxcala, Puebla, Veracruz, Chiapas, and Yucatan the individual perception of insecurity considerably increased. Notably, in 2011, citizens from Queretaro had a 30% chance of feeling insecure and, by 2016, the probability increased to 62%.

Figure 10. Change in the Predicted Probabilities of Feeling Insecure by State, 2011-2016

Source: Stanford Poverty, Violence and Governance Lab with data from ENVIPE 2011-2016. Scales goes from dark green to dark red. Green states show a negative change in the probability from 2011 to 2016 and states in red show the states in which an individual's probability increased.

On the other hand, regarding the estimated probability of suffering any kind of crime, Figure 11 shows that most of the probabilities are higher in 2015 than in 2010. The map also shows that

Chihuahua, Sinaloa, and Nuevo Leon, along with improving of their perception of security, also decreased individuals' probability of suffering a crime. Notably, the map shows that the northern region of the country appears to be safer in 2015 than in 2010 and that the Tierra Caliente region—Jalisco, Colima, Michoacan, Estado de Mexico, Guerrero, and Morelos—hosts the biggest increases in the predicted probability of suffering a crime.

One interesting finding is that states that have typically been associated with high violent crime rates related to DTOs – Sinaloa, Chihuahua, Nuevo Leon, and Tamaulipas – present some of the lowest probabilities of suffering a crime in 2016. Nevertheless, it is important to be cautious about the interpretation of these changes. States in green do not necessarily reflect good practices. Decreases presented in recent years might solely be reflecting that perceptions of insecurity and victimization were, in fact, very high in 2011.

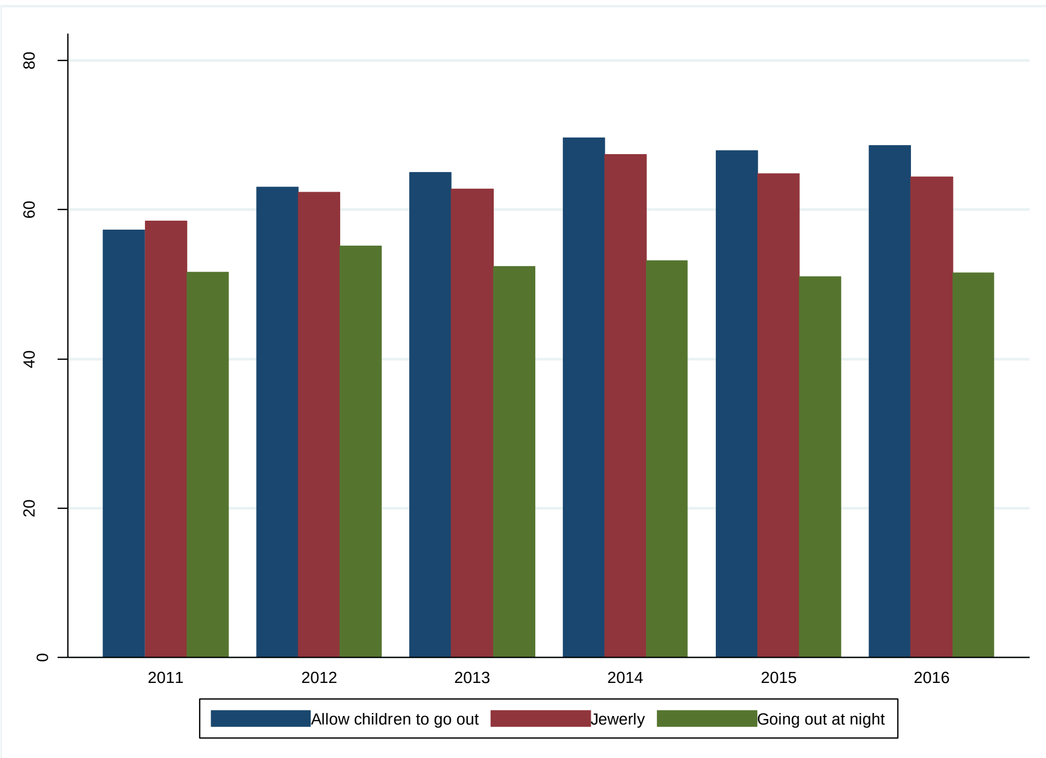
Figure 11. Change in the Predicted Probabilities of Being Victim of a Crime by State, 2011-2016

Source: Stanford Poverty, Violence and Governance Lab with data from ENVIPE 2011-2016. Scales goes from dark green to dark red. Green states show a negative change in the probability from 2011 to 2016 and states in red show the states in which an individual's probability increased.

Individual Responses to Crime

Crime rates have increased in Mexico since 2011 and the majority of Mexicans are concerned about insecurity in the country and feel insecure in their states. This raises the question of whether Mexicans have changed their behavior out of fear of crime. ENVIPE's data suggest they have. Since 2011, more than 50% of the population reported having stopped allowing children to go out, wearing jewelry, and going out at night. Figure 12 shows that while avoiding going out at night has remained constant with time, there is an increasing fear that the environment of crime and insecurity could affect children. Since 2012, children's safety has been the biggest concern of Mexicans at the national level.

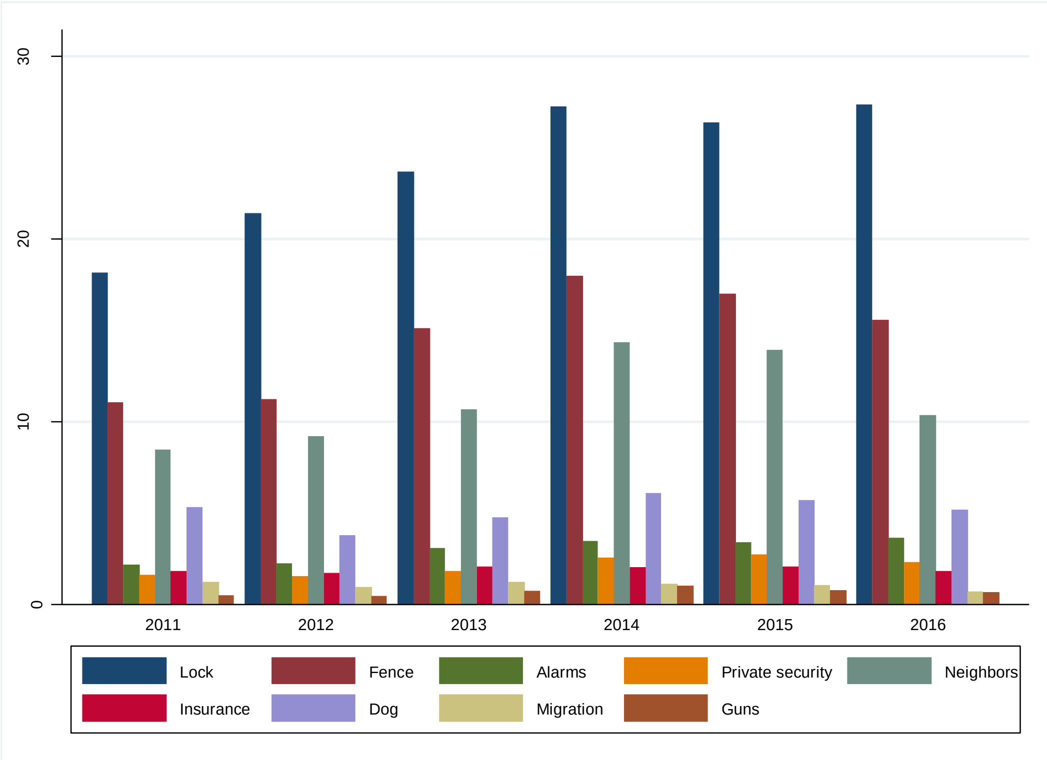
Figure 12. Main Avoided Activities out of Fear of Crime, % of population



Source: Stanford Poverty, Violence and Governance Lab with data from ENVIPE 2011-2016.

Moreover, according to the survey, Mexicans are not only avoiding activities, but they are in fact taking actions against crime. Figure 13 indicates that when individuals take measures to protect themselves, they resort to changing the lock of their houses, building a fence to protect themselves, or organizing with neighbors. The figure shows that the percentage of population performing these three activities is higher now than six years ago.

Figure 13. Most Common Measures Taken to Improve Security, % of population



Source: Stanford Poverty, Violence and Governance Lab with data from ENVIPE 2011-2016.

Because we know that perceptions of crime vary across socioeconomic groups, we would also expect to see variations in terms of how each group responds to crime. More specifically, we would like to answer which individuals prefer to invest in the household infrastructure and which ones prefer to organize with the community. For this purpose, we performed an analysis at the individual level of how individual responses to crime relate to socioeconomic background, individual victimization, neighborhood quality, and state and police presence.

Although we ran logistic models for all the measures taken to improve security, or "self-help activities", in this subsection, we specifically focus on the probabilities of changing the lock of the house and organizing with neighbors (see Appendix for further details). We chose these two variables because, according to Figure 13, changing the locks is Mexicans' preferred option and organizing with neighbors could provide some context on how much citizens engage with their communities and/or trust their neighbors.

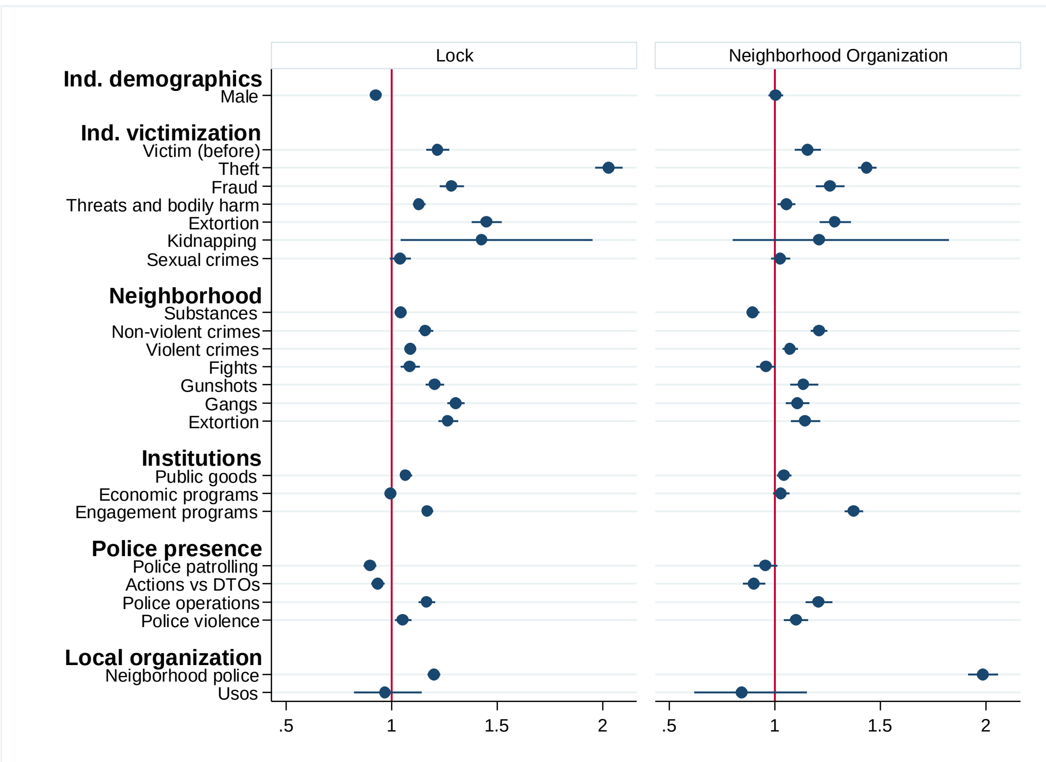
Similar to the individual analysis of perceived insecurity and victimization, we begin with the analysis of the covariates related to victimization, neighborhood characteristics, state and police presences, and local forms of organization. Then, we focus on the differences in the predicted probabilities of self-helping across socioeconomic backgrounds.

Figure 14 shows the estimated size effects of changing the lock and organizing with neighbors. The logistic estimates indicate that males are less likely to decide to change the lock than females, while gender does not matter in the decision of organizing with neighbors. Both models indicate that being the victim of a crime increases the probability of taking action to fight insecurity, especially if the crime was theft. However, being kidnapped is not associated with organizing with neighbors and being a victim of sexual crimes does not affect either of the two responses. In fact, victims of sexual crimes behave differently from the rest of the victims in all the self-help models. As shown in the Appendix, this variable is either not significant at the 95% or is associated with decreases in the probability of putting alarms or video vigilance. This is not surprising because sexual crimes are not something that can be prevented given that the perpetrators and the victims often know one another. Furthermore, because sexual violence overwhelmingly goes unreported, people may not be able to outwardly take steps to combat this particular fear. In the second part of the report, when analyzing the determinants of interpersonal distrust, we further detail the dynamics of sexual crimes and their relationship with citizen perceptions of violence and police.

Neighborhood characteristics are also significant in the decision of responding to perceptions of insecurity. In the case of changing the lock, the highest coefficients occur when there are gangs and cases of extortion present in the neighborhood. These effects are similar to the neighborhood organization model, with the exception that the sale and consumption of substances and the presence of fights between neighbors also decrease its probability.

Living under Usos y Costumbres[6] does not correlate with changing behaviors out of fear of crime. However, individuals living in communities where neighbors have created a neighborhood police or hired a private police are more likely to also change the lock of their house and organize with neighbors. The state, through the provision of public goods and programs, is generally associated with increases in the probability of self-helping. We believe that public resources are likely being allocated to dangerous neighborhoods where individuals are already choosing to defend themselves. Nevertheless, state presence, through police patrolling and actions against DTOs, does appear to be an effective measure to keep citizens feeling safe and without modifying their behavior out of fear of crime.

Figure 14. Estimated Effect Sizes of Changing Lock and Organizing with Neighbors

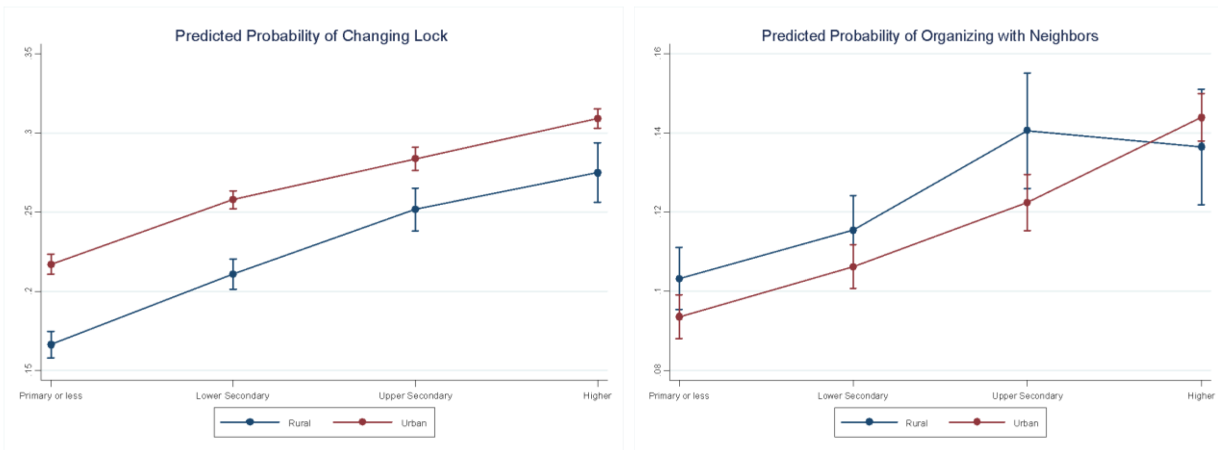


Note: Logit models with state and year FE and the interaction of both terms. 95% confidence intervals. Clustered standard errors by municipality. Observations weighted by survey weights. Models are also controlled for age, employment status, and family size. Further details of the estimation in the Appendix.

[6] Usos y Costumbres communities have full legal standing to a form of traditional indigenous governemnts, which entails electing individuals to leadership positions through customary law in non-partisan elections, making decisions through participatory democracy, and monitoring compliance through a parallel (and often informal) system of law enforcement and community justice.

Regarding the effect of the socioeconomic background, Figure 15 shows that the predicted probability of changing lock is slightly similar, in terms of trend and size, to the predicted probability of suffering a crime (Figure 9). Moreover, for both self-help activities, highly educated individuals have higher chances of self-helping than the least educated ones. However, while urban individuals are more likely to change their lock than rural citizens, there is no significant difference between the two in terms of the probability of neighborhood organization,

Figure 15. Predicted Probabilities of Changing Lock and Organizing with Neighbors by Socioeconomic Status



Predictive Margins with 95% confidence intervals. Further detailed in the Appendix.

Summary

ENVIPE is one of the most useful tools to understand the dynamics of crime and how it affects citizens' life. By providing a state-representative data – with information from citizens ages 18 or older –, it aims to facilitate the understanding of victimization and how citizens perceive issues related to crime. This section was intended to provide a general overview of the perception of insecurity, crime, and changes in individual behaviors due to fear of crime. After performing descriptive and statistical analyses, we conclude the following about variations of perceptions across individuals, states and time.

First, Mexicans are aware of the security crisis that the country is experiencing and consider it one of the greatest problems, at least since 2011. However, perceiving security as a national issue does not necessarily imply that all individuals feel insecure in their states or that all the states share similar victimization rates. As a first approach, our analysis shows that there might be a positive correlation between feelings of insecurity and victimization rates. However, there are some states where the correlation does not hold. Therefore, we argue that crime perceptions are better explained by three general hypotheses: a) individual specific characteristics – particularly, socioeconomic status – and victimization experiences can explain differences in crime perceptions across individuals, b) individuals living in dangerous neighborhoods are more likely to feel insecure or report having been the victim of a crime, and c) state presence and police presence – public goods provision, police patrolling, and actions against DTOs – are effective at decreasing individual perceptions of security and crime.

Second, we showed that around a quarter of the population has been the victim of crime, which is above the levels of other Latin American countries, and that this is changing individuals' behavior. For example, people are avoiding going out at night, wearing jewelry, and letting children go out alone. In addition, on average, victimization, particularly, being a victim of theft, is associated with individuals changing the lock of their house or organizing with neighbors to fight insecurity. In both cases, the individuals that are more likely to act are the most educated ones.

Third, some states are more violent than the rest. After controlling for individual, local and institutional characteristics (and state and time fixed effects), we showed that the northern states

seem to be improving their perceptions of security and reducing their victimization rates. However, states in the central and southern Pacific regions – particularly states in the Tierra Caliente region – have been experiencing higher victimization rates.

Fourth, the individual level analysis shows that demographic characteristics matter in the determination of all perceptions. Based on our findings, we argue that crime and insecurity do not uniformly affect the entire population and that there are certain groups that can be more affected by violence than others. The models show that there are clear differences between individuals in urban and rural settings, with urban residents being more victimized and rural feeling more insecure. Furthermore, we find differences based on educational attainment: highly educated individuals are more likely to be victimized and take more self-help actions than the least educated ones.

Fifth, neighborhood characteristics and state and police presence are significant determinants of crime perceptions. On one hand, dangerous neighborhoods associate positively with higher chances of feeling insecure and suffering a crime. On the other hand, public interventions can highly improve citizen crime perceptions. Specifically, police patrolling and institutional actions against DTOs – with the exception of police operations – are very effective in decreasing the chances of feeling insecure and being victimized. So far, local forms of organization, such as living under an Usos y Costumbres government, does not seem to determine individual perceptions of crime.

In the next section, we focus on the descriptive and statistical analysis of citizen satisfaction with police performance. We analyze citizen perceptions on police ineffectiveness, corruption, and trustworthiness, with a special emphasis on the importance of trust in the determination of police legitimacy.

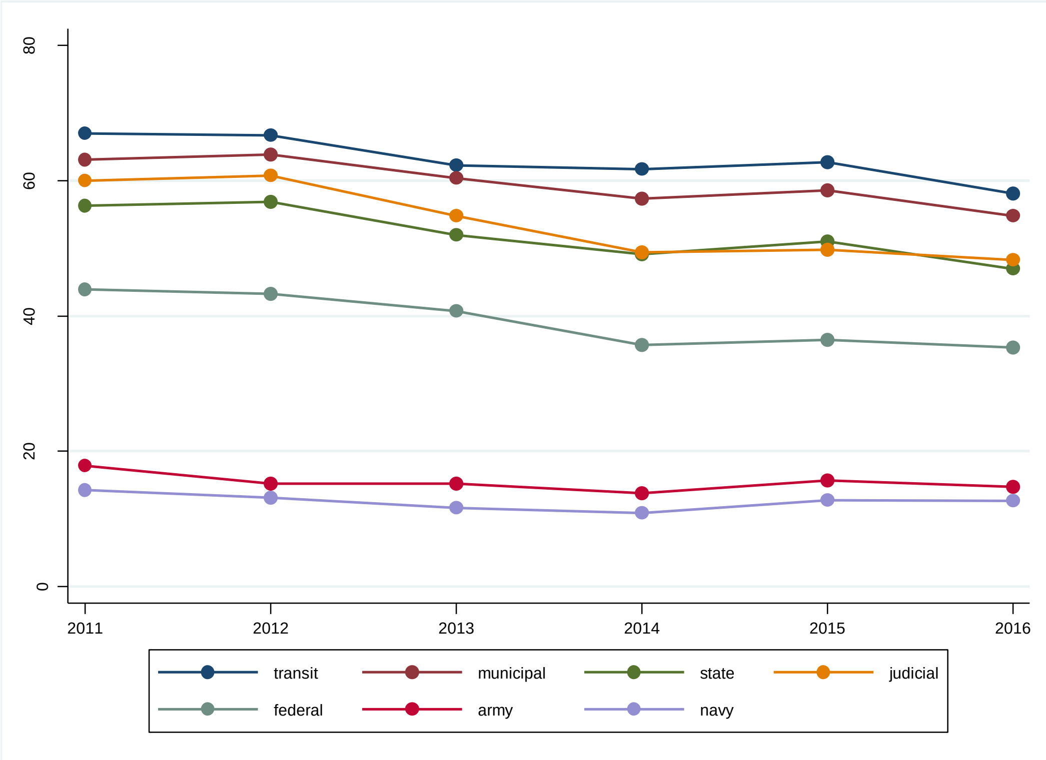
II. Citizen Satisfaction with Police Performance

In the previous section, we showed that the majority of Mexicans report feeling insecure in their state, a third of them report having been the victim of a crime, and a similar percentage report having changed their behavior out of fear of falling victim to a crime. In addition, we showed that there is a large variation in crime perceptions across states, settings, and socioeconomic groups. Nonetheless, we also showed that police patrolling and governmental actions taken against DTOs – excluding police operations – could be effective mechanisms for improving citizen perceptions of security. In this part of the report, we will focus on police actions and the way their behavior is perceived by citizens. Particularly, our analysis will focus on citizens' perception of municipal police ineffectiveness, corruption, and trustfulness.

Citizen Perception of Police Ineffectiveness and Corruption

ENVIPE measures police performance by asking individuals whether they consider police to be "very effective", "effective", "ineffective", or "very ineffective". In Figure 16, after grouping "very ineffective" and "ineffective" responses into one category and "very effective" and "effective" into another one, we graph the changes in these responses across time and for different police levels. As seen in the figure, citizen perception of ineffectiveness has smoothly decreased since 2011, with the biggest decreases presented between 2012 and 2014. More importantly, the figure shows that Mexicans generally have lower opinions of the most local police forces, while finding army and navy to be highly effective. Around 60% of the population considers that transit and municipal police are ineffective and more than 80% considers that the navy and the army are effective.

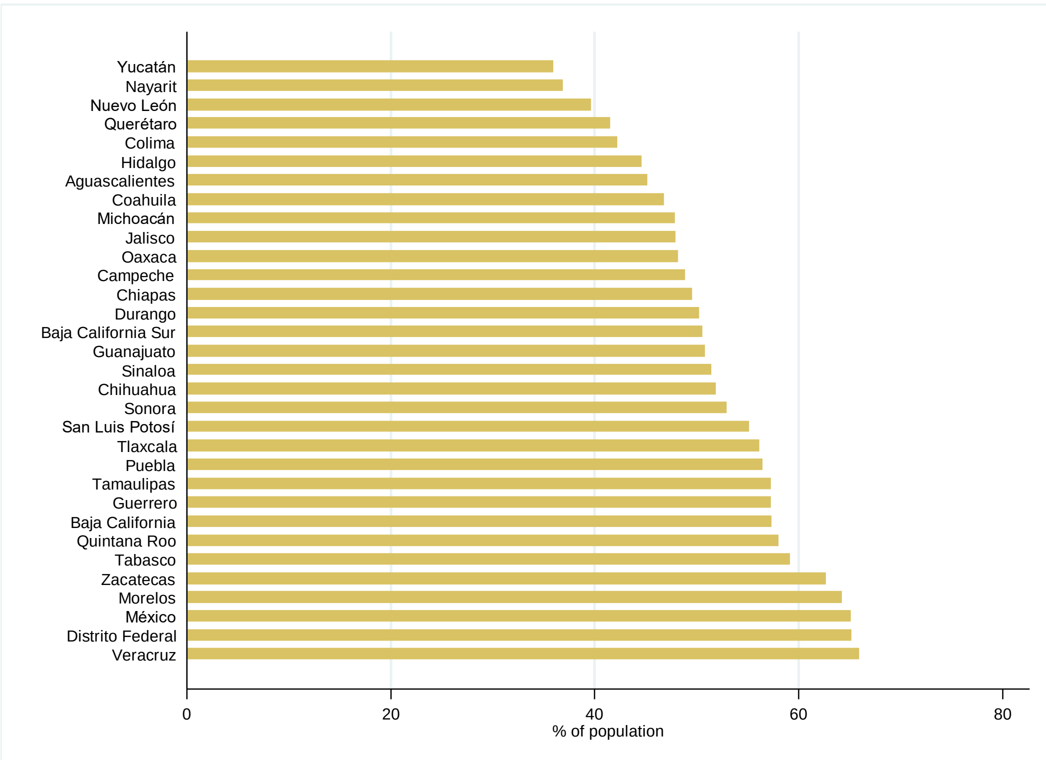
Figure 16. Perception of Ineffectiveness by Level of Police, % of population



Source: Stanford Poverty, Violence and Governance Lab with data from ENVIPE 2011-2016.

Because municipal police oversee the prevention and control of daily crime and, in some cases, is in charge of transit activities, we only focus on this police level for the 2016 state comparisons and the econometric analyses of police ineffectiveness and corruption. Figure 17 confirms what we have already observed throughout this report: state-level rates can differ greatly from national-level ones. For example, in 2016, at the country level, the ineffectiveness rate of municipal police was close to 60%, while, at the state level, the rates ranged from 35% to 65%. More than 60% of the population of both Nayarit and Yucatan consider their municipal police as effective, while less than 40% of the populations in Veracruz, Distrito Federal, Mexico State, and Morelos approve of their local police's performance. It is important to note the cases of Nuevo Leon and Veracruz. In 2016, even though Nuevo Leon's population suffered from high victimization and feeling of insecurity rates, those living there considered the municipal police to be fairly effective. In the case of Veracruz, where victimization rates are low but the feeling of insecurity is above 80%, the ineffectiveness rate ranks first in the country. In fact, in Veracruz, there is a larger correlation between citizen satisfaction with police and citizen perception of insecurity than between citizen satisfaction and victimization rates. Veracruz, Distrito Federal, Mexico, Morelos, Zacatecas, and Tabasco rank all as both the states with the most ineffective municipal police and as those with the largest percentage of the population that feels insecure in their state.

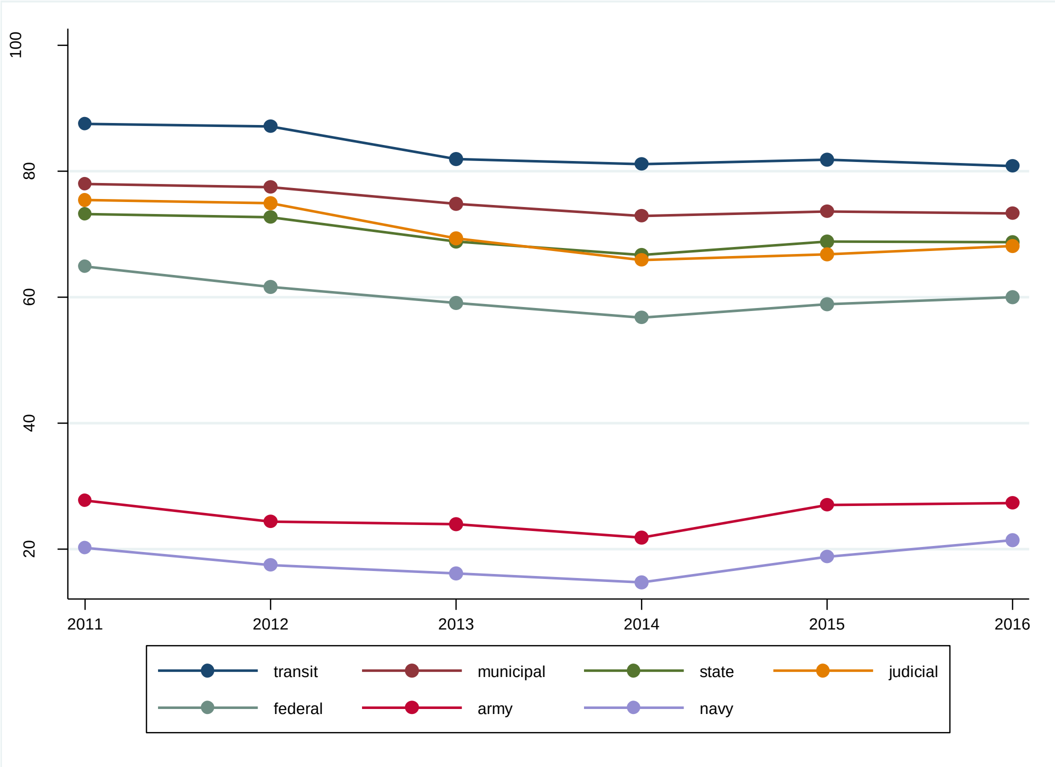
Figure 17. Perception of Municipal Police Ineffectiveness, 2016



Source: Stanford Poverty, Violence and Governance Lab with data from ENVIPE 2011-2016.

ENVIPE also measures citizen satisfaction with the police by asking individuals about perceived levels of police corruption. To measure this, ENVIPE directly asks individuals if they consider police officers to be “corrupt” or “not corrupt”. Figure 18 shows that, similar to the perception of ineffectiveness, individuals prefer federal forces over more local ones; in fact, corruption preferences are ordered in the same way as effectiveness preferences. For municipal police in 2016, around 75% of the people considered police officers to be corrupt. For the navy and army, these percentages were below 30%. Interestingly, perceived corruption rates for local-level police have remained steady in the last 4 years, while perceived corruption rates for the army, navy and federal police have all been increasing since 2014.

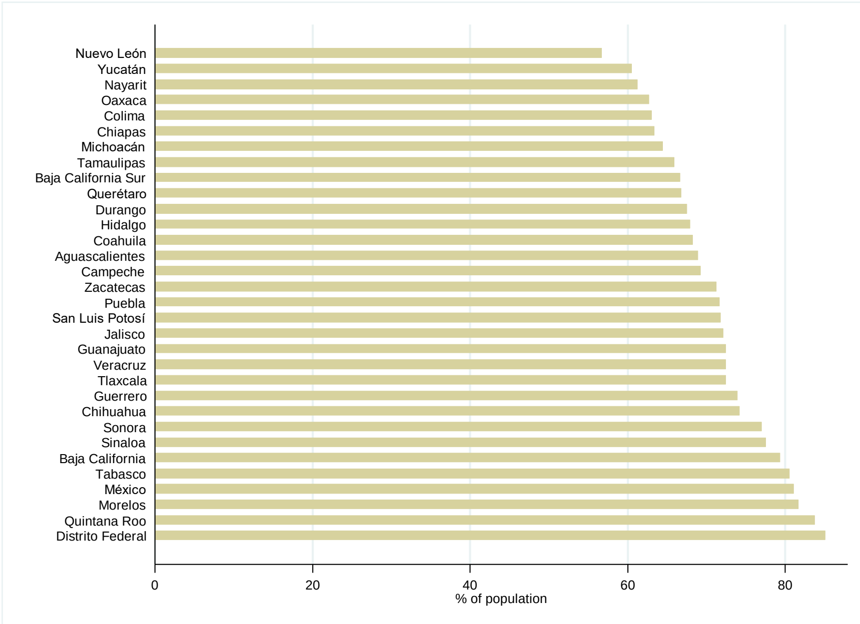
Figure 18. Perception of Corruption by Level of Police, % of population



Source: Stanford Poverty, Violence and Governance Lab with data from ENVIPE 2011-2016.

When comparing 2016 corruption rates across states, Nayarit and Yucatan once again appear among the list of states with the best-perceived municipal police officers. Similarly, Nuevo Leon shows again that, even though its citizens are worried about insecurity, they believe that the majority of their municipal police forces are effective and non-corrupt. At the other extreme of the rankings, Distrito Federal appears to have the most corrupt local police with more than 80% of the population perceiving them to be corrupt.

Figure 19. Perception of Municipal Police Corruption, 2016



Source: Stanford Poverty, Violence and Governance Lab with data from ENVIPE 2011-2016.

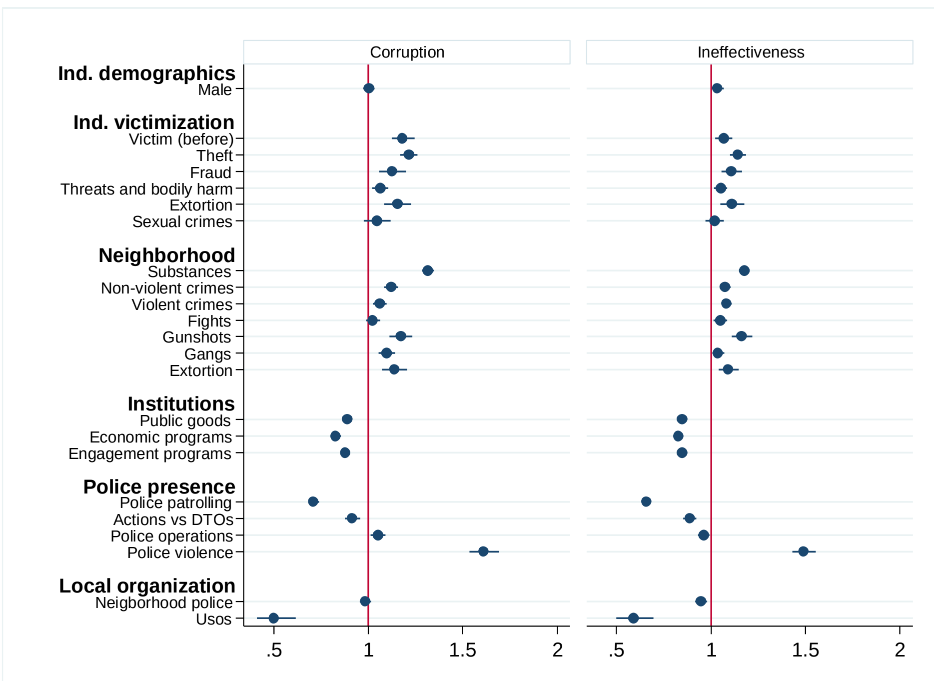
Are citizen perceptions of police determined the same way as perceptions of insecurity and victimization rates?

When analyzing ENVIPE information at the individual level, we identified several sociodemographic, local, and institutional factors that are associated with citizens' perceptions, experiences, and decisions. In Figure 20, we show the estimated effect sizes of two logistic models of citizen perceptions of municipal police corruption and ineffectiveness. Both models are analogous to the specifications used when we analyzed feelings of insecurity, victimization, and self-help activities.

Figure 20 shows that gender is not a relevant factor in determining the perception of corruption. However, for ineffectiveness, males are more likely to disapprove of the municipal police. Moreover, the more dangerous the neighborhood, the more likely it is that individuals consider the municipal police as corrupt or ineffective. For both models, the sale or consumption of substances holds the highest correlation with dissatisfaction with the police. In terms of victimization, both models show that all the crimes are associated with increases in both probabilities, except in the case of sexual crimes.[7] Interestingly, being the victim of a sexual crime – sexual harassment or rape – does not seem to be strongly associated with any of the perceptions we have analyzed so far.

In terms of state and police presence, all the public programs decrease the probability of disapproving municipal police. Citizen perceptions seem to especially benefit from police patrolling. This relationship, together with the estimate of police violence – which is the highest in both models – suggests that citizen satisfaction with police is a function of police performance itself. The importance of police performance is also reflected in the estimated effect of living in Usos y Costumbres communities. In these communities, where police respond to local traditions, citizens are around 50% less likely to consider police officers as corrupt or ineffective when compared to citizens living in communities ruled by political parties.

Figure 20. Estimated Effect Sizes of Perception of Municipal Police Corruption and Ineffectiveness



Note: Logit models with state and year FE and the interaction of both terms. 95% confidence intervals. Clustered standard errors by municipality. Observations weighted by survey weights. Models are also controlled for age, employment status, and family size. Further details of the estimation in the Appendix.

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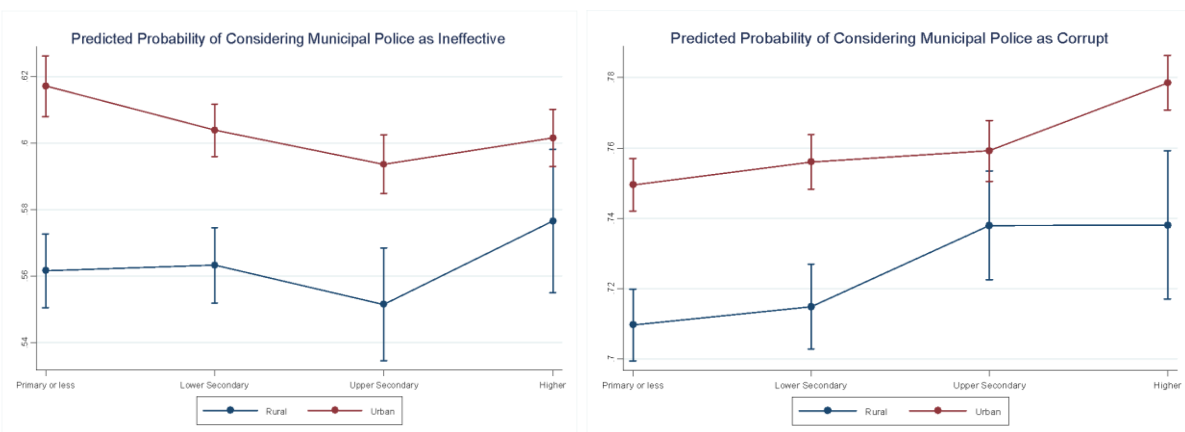
[7] For visualization purposes, the coefficient of kidnapping is not shown in the graph. As shown in the appendix, being a victim of this kind of crime highly increases the probability of considering municipal police as corrupt, but has no impact on its perception of ineffectiveness.

In terms of variations across socioeconomic groups, Figure 21 shows that, similar to other citizen perception about security and crime, satisfaction with municipal police varies across rural and urban groups, with urban individuals showing, on average, higher chances of disapproving of municipal police performance. In terms of ineffectiveness, although the variation in the predicted probabilities across levels of education is not clear, the figure suggests that the probability does not increase with years of schooling. In fact, it shows that the least educated urban individuals might have higher chances of considering the police ineffective than the highly educated ones in this kind of setting.

In the case of citizen perception of corruption, the effect of years of schooling on urban citizens is clearer than for those that live in urban communities. Individuals from urban settings that have attained at least one year of higher education are more likely to consider municipal police corrupt than the least educated urban citizens and rural citizens. For rural individuals, differences across levels of education are not clear. Nonetheless, the graph suggests that individuals with at least one year of upper secondary education have higher chances of considering police corrupt than the least educated ones.

Figure 21. Predicted Probabilities of Perceptions of Municipal Police by Socioeconomic Status



Predictive Margins with 95% confidence intervals. Further detailed in the Appendix.

Figures 22 and 23 map how the predicted probabilities of considering municipal police ineffective or corrupt changed from 2011 to 2016 according to our models. The first map indicates that almost all states, with the exception of Baja California, Guanajuato, Veracruz, and Chiapas had better perceptions of police effectiveness in 2016 than in 2011. The state that managed to decrease its ineffectiveness rate the most is Nuevo Leon, while the state with the largest increase in this rate is Chiapas. It is important to recall that in 2016, both states presented an ineffectiveness rate below the national rate.

Figure 22. Change in the Predicted Probabilities of Municipal Police Ineffectiveness by State, 2011-2016

Source: Stanford Poverty, Violence and Governance Lab with data from ENVIPE 2011-2016.

Unlike the change in states' perceptions of ineffectiveness, where most states present decreases in the rate, Figure 23 shows that there is no clear trend in the changes in states' corruption rates. While Aguascalientes, Hidalgo, and Sinaloa greatly improved their citizen perception of municipal police corruption from 2011 to 2016, Oaxaca, Tabasco, and Queretaro presented significant decreases.

Figure 23. Change in the Predicted Probabilities of Municipal Police Corruption by State, 2011-2016

Source: Stanford Poverty, Violence and Governance Lab with data from ENVIPE 2011-2016.

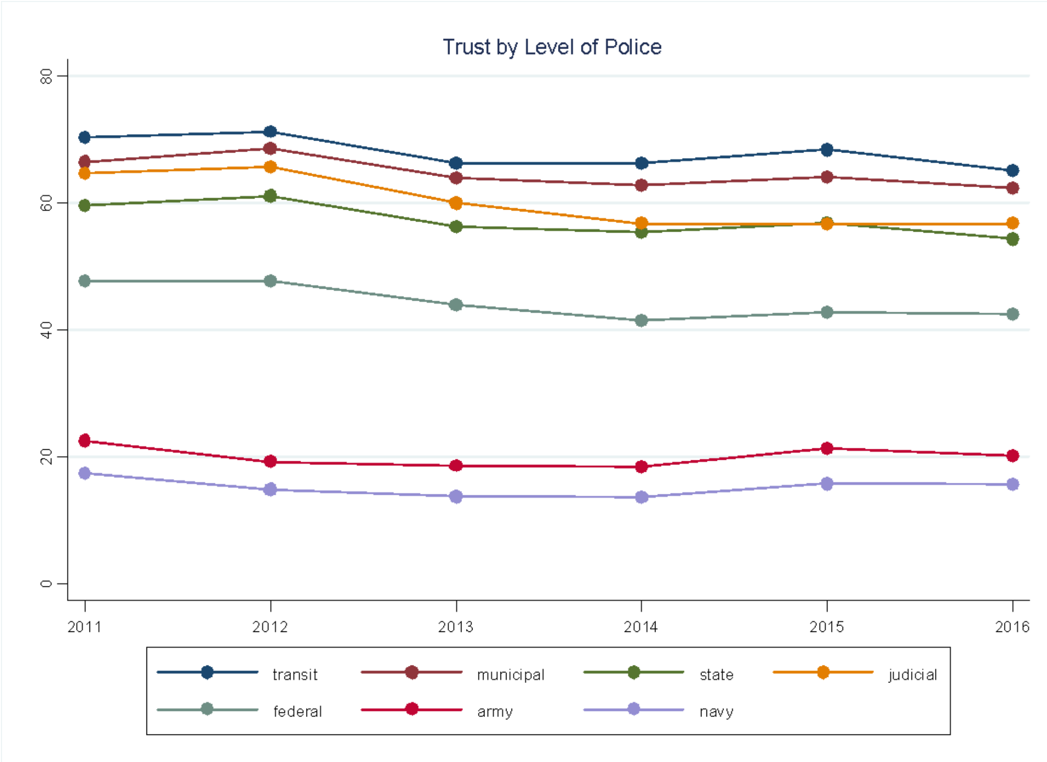
Citizen Distrust of Police

The previous section allowed us to identify that citizen perceptions of police corruption and ineffectiveness behave similarly to perceptions of insecurity and crime, with individual, neighborhood and institutional factors highly affecting their levels. In this section, we focus on citizen distrust of police. Because we believe that trust in police is a necessary condition for citizen cooperation and effective law enforcement, in the next pages, we analyze citizen distrust across all levels of police, states, socioeconomic groups, individuals, and time.

In Figure 24, we graph how national distrust in local and federal levels of police has varied since 2011. The figure shows that distrust levels have declined slightly since 2011, with the biggest drops occurring between 2012 and 2014. The graph confirms what the analysis of citizen perception of corruption and ineffectiveness suggested: Mexicans have lower opinions of the most local police forces while they consider the army and navy to be highly trustworthy. Currently, around 70% of the population distrusts transit and municipal police, while only about 20% of people distrust the army and navy.

When comparing levels of distrust, ineffectiveness, and corruption, we find that around 70% of people distrust local police levels or consider them ineffective, while 75% consider them corrupt. This difference between perceptions could be explained by the way in which ENVIPE measures each variable. Questions regarding ineffectiveness and distrust include four possible answers, while the question about police corruption only includes two options. It is also possible that people have stronger opinions on or a clearer concept of police corruptibility than on its ineffectiveness or trustworthiness.

Figure 24. Distrust of Police by Level of Police, % of population



Source: Stanford Poverty, Violence and Governance Lab with data from ENVIPE 2011-2016.

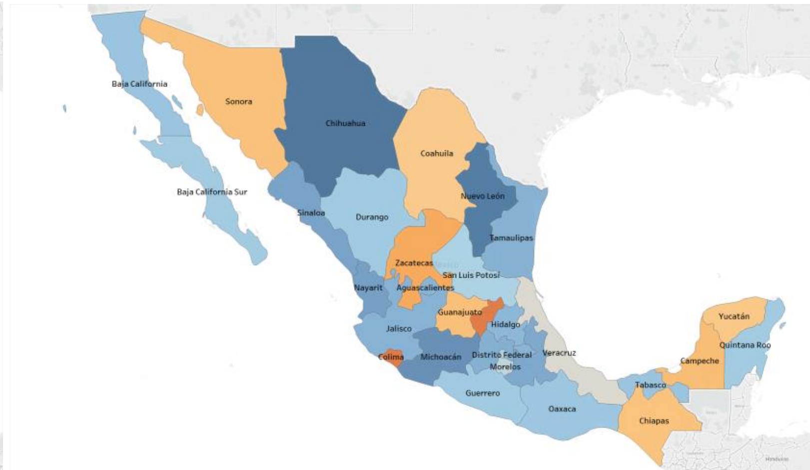
The increase in trust at the national level does not necessarily mean that every state in the country has seen an increase in its residents' trust in the authorities. The maps in Figure 25 show the percentage change in distrust in police from 2011 to 2016. The scale goes from dark orange to dark blue, with states in orange presenting the highest increases in distrust of police and states in blue showing the largest decreases in this variable. Because the national average appears to show a decrease in citizen distrust at all levels during the period in question, it is not surprising that Figure 25 shows more blue states than orange states. Nevertheless, the maps show that an increased trust in police has not been a uniform phenomenon. Some states that managed to increase trust at a specific level of law enforcement have not necessarily been able to increase trust in other branches.

For example, Nuevo Leon had the largest decline in distrust of municipal and state police, while also having the greatest increases in distrust of the army and the navy. Oaxaca and Chiapas show growing distrust of municipal police, while increasing trust in federal police and the army. Zacatecas appears to be moving towards trusting their municipal police, while also moving towards distrusting their state and federal police. Their distrust of the army and navy is among the highest among Mexico's states. Moreover, Colima, whose trust of all levels of police, in absolute terms, is higher than the national average, presents the greatest increase in distrust of municipal police from 2011 to 2016. In addition, Colima is one of the few states that was unable to reduce its distrust levels in the analyzed period.

Figure 25. Percentage Change in Distrust at the State Level, 2011-2016

Municipal

State



Federal

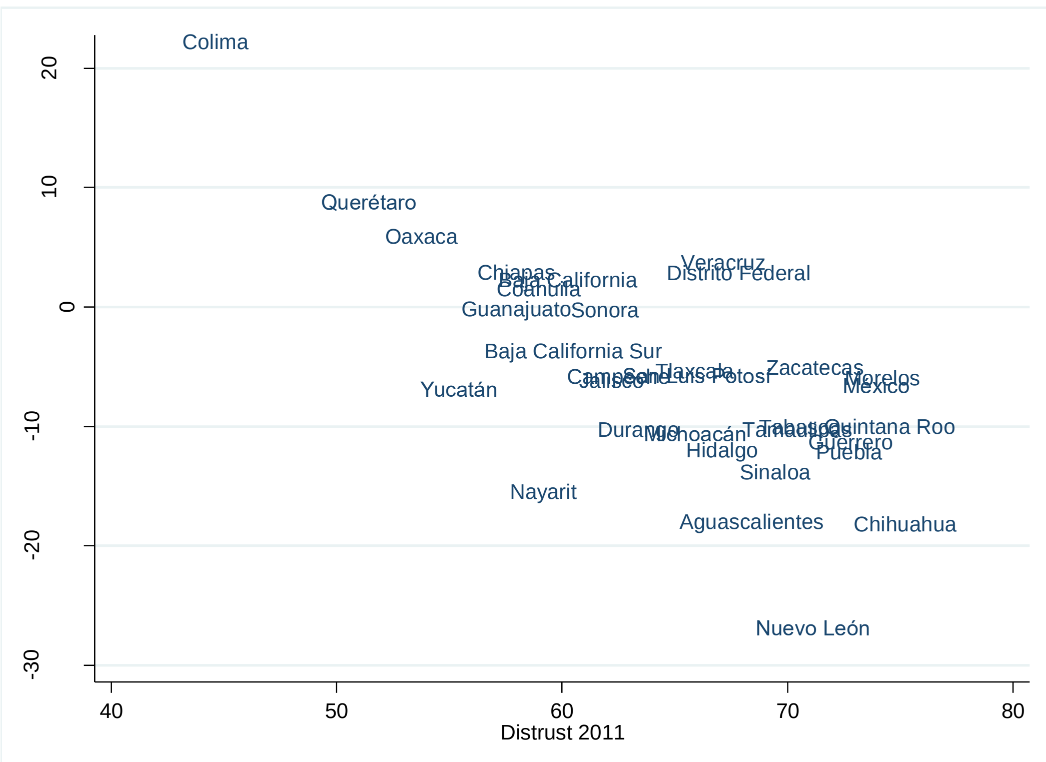
Army

Navy

Source: Stanford Poverty, Violence and Governance Lab with data from ENVIPE 2011-2016. Scale goes from dark blue to dark orange, with states in blue showing decreases in distrust and states in orange showing increases in distrust.

To better understand how the distrust of municipal police has varied from 2011 to 2016 and to identify which states have undergone the most change, we use Figure 26 to specifically compare the rates of distrust of the municipal police in 2011 with the change in this percentage from 2011 to 2016. The graph shows that, in 2011, Colima, Queretaro, Oaxaca, and Yucatan had the lowest rates of distrust, while Chihuahua, Quintana Roo, Morelos, and Mexico had the highest levels. Moreover, the graph displays that, in 2011, Nuevo Leon and Chihuahua had two of the most distrusted local police forces. Nevertheless, by showing that highly distrusted states managed to improved distrust rates and that states like Colima increased distrust levels, the graph suggests that states are converging to similar levels of citizen distrust. Furthermore, the graph provides some insight on good and bad practices. On one hand, Yucatan and Nayarit started with low levels of distrust and have been decreasing it since then. On the other hand, Veracruz and Distrito Federal, in 2011, had distrust rates around 70% and a positive growth rate.

Figure 26. Distrust and Change in Distrust by State, 2011-2016



Source: Stanford Poverty, Violence and Governance Lab with data from ENVIPE 2011-2016.

In terms of individual experiences and how they correlate to the three hypotheses that guide this report, in Figure 27, we show the estimated effect sizes of predictors of distrust at all levels of police. Overall, the models show that individual victimization, neighborhood deterioration, and police violence are usually associated with higher chances of distrusting police forces. In addition, we observe that public institutional programs and police presence generate the opposite effect by decreasing the likelihood of distrusting police. Although these relationships were expected, given the models of police corruption and ineffectiveness, there are specific correlations that require further discussion.

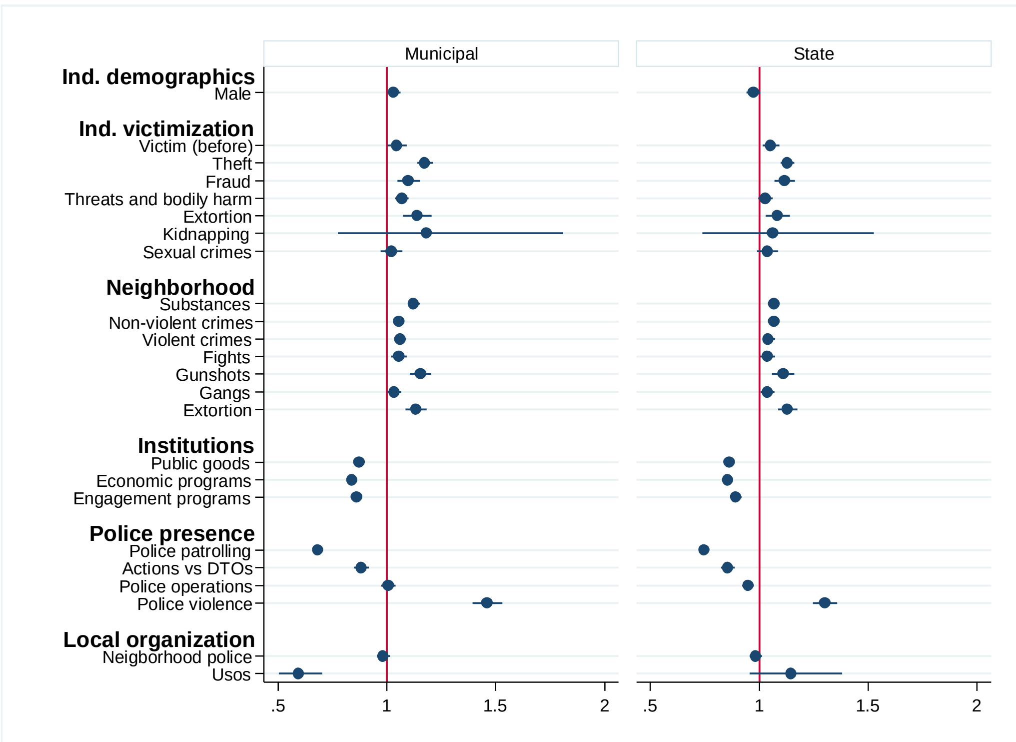
The male population, which is more likely to be victimized by the police but less likely to feel insecure in comparison to females, has a high probability of distrusting municipal police but a lower probability of distrusting other police forces, particularly the navy and the army. Second, although crime victims hold a higher probability of distrusting all levels of police, prior victimization has a significant, negative effect on distrust of navy, suggesting that individuals whom were previously victimized value the intervention of the navy. Third, sexual crime victims' distrust levels only differ significantly from those of non-victims in the army model, where having suffered this kind of crime increased the likelihood of distrusting army.

Fourth, neighborhood characteristics correlate more with distrust of municipal police than with any other police levels – except in the case of fights between neighbors, which considerably increases the probability of distrusting the navy and the army. Fifth, in terms of institutional development, the provision of public goods is the main factor behind decreases in distrust of federal forces. For municipal and state police, economic programs appear to be as important as public goods.

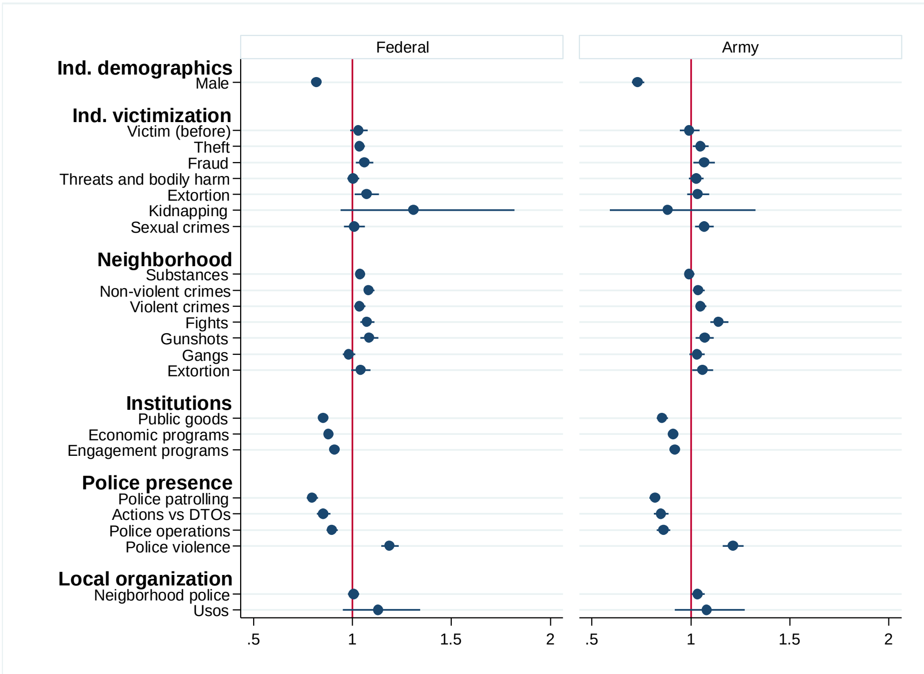
Sixth, all the models confirm that police presence, particularly through police patrolling, is potentially the most effective way of decreasing distrust of police forces, especially in the case of municipal police. Unlike previous models, where police operations increased the probabilities of feeling insecure, being victimized or considering municipal police to be corrupt, police operations seem to decrease the probabilities of distrusting local and federal authorities. Regarding police violence, in all cases, it is associated with high levels of distrust, but it is most impactful for levels of distrust of municipal police.

Seventh, in terms of local forms of organization, the presence of neighborhood police does not seem to be associated with distrust of any other level of police and communities organized under Usos y Costumbres regimes are 40% less likely to distrust municipal police officers. The null association between this type of regime and the distrust of the other police forces was expected because those do not vary between Usos and non-Usos localities.

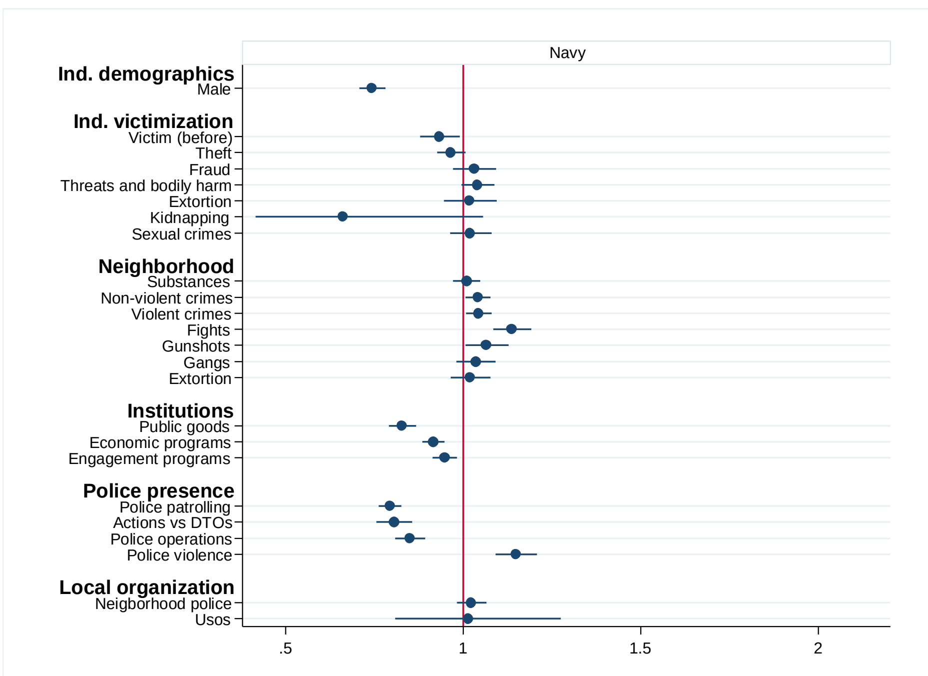
Figure 27. Estimated Effect Sizes of Distrust of Police by Level of Police



Note: Logit models with state and year FE and the interaction of both terms. 95% confidence intervals. Clustered standard errors by municipality. Observations weighted by survey weights. Models are also controlled for age, employment status, and family size. Further details of the estimation in the Appendix.



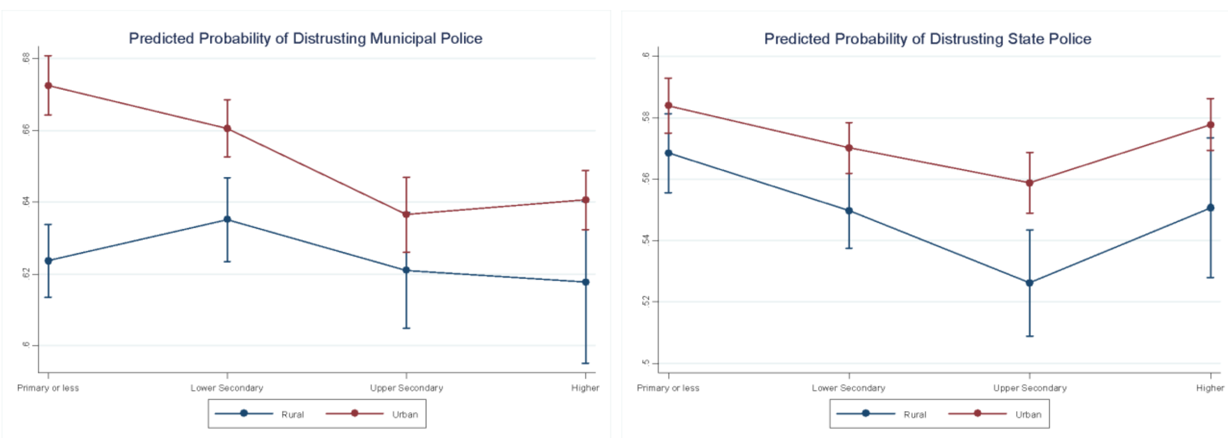
Note: Logit models with state and year FE and the interaction of both terms. 95% confidence intervals. Clustered standard errors by municipality. Observations weighted by survey weights. Models are also controlled for age, employment status, and family size. Further details of the estimation in the Appendix.



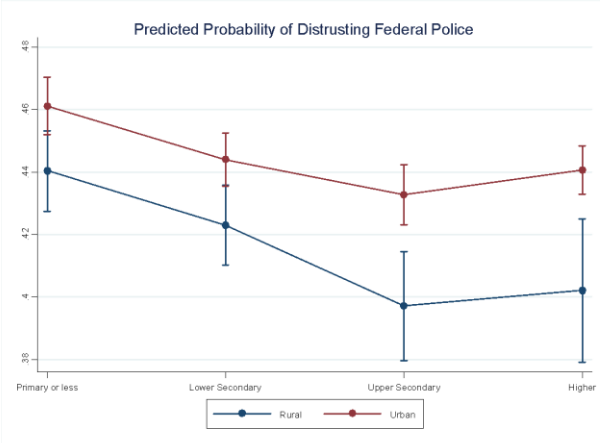
Note: Logit models with state and year FE and the interaction of both terms. 95% confidence intervals. Clustered standard errors by municipality. Observations weighted by survey weights. Models are also controlled for age, employment status, and family size. Further details of the estimation in the Appendix.

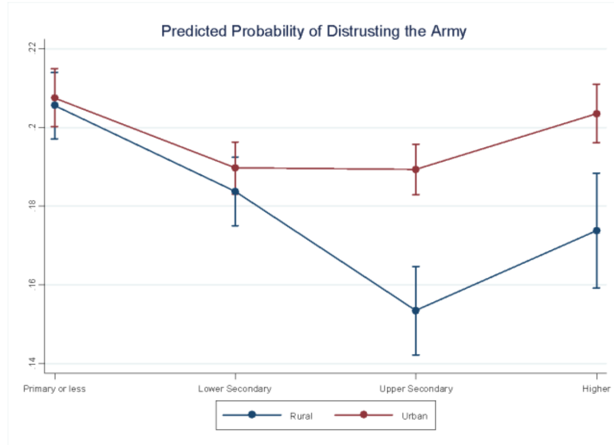
In the previous sections, we provided evidence that moderately suggests that years of education increases the likelihood of feeling insecure, being victimized, changing behavior, and disapproving of police performance in terms of municipal police ineffectiveness and corruption. However, in the case of citizen distrust of police, the graphs from Figure 26 suggest an inverse relationship. Although it is not consistent across all levels of education, individuals with fewer years of schooling show the highest probability of distrusting police forces. In other words, educational attainment might be decreasing the probability of distrusting police.[8] Furthermore, if we assume that individuals with low levels of education come from disadvantaged socioeconomic groups, the graphs suggest that their relationship with the police is different from the one police has with less disadvantaged individuals. This divergence is interesting because advantaged socioeconomic groups are, in fact, more likely to be victimized, feel insecure, and consider police corrupt than the most disadvantaged ones.

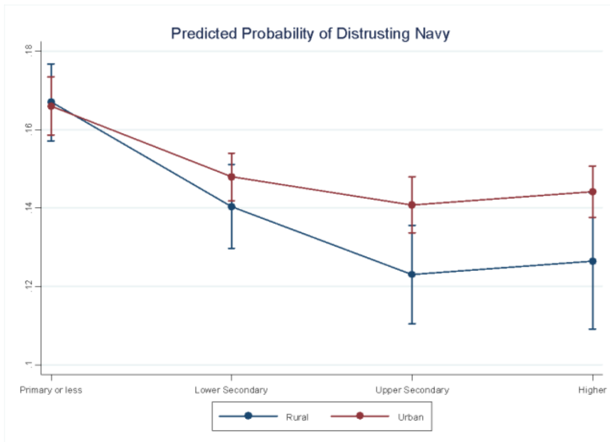
Figure 28. Predicted Probabilities of Distrust of Police by Socioeconomic Status



[8] The perception of ineffectiveness showed a similar behavior, but the confidence interval did not allow us to see clear differences between levels of education.







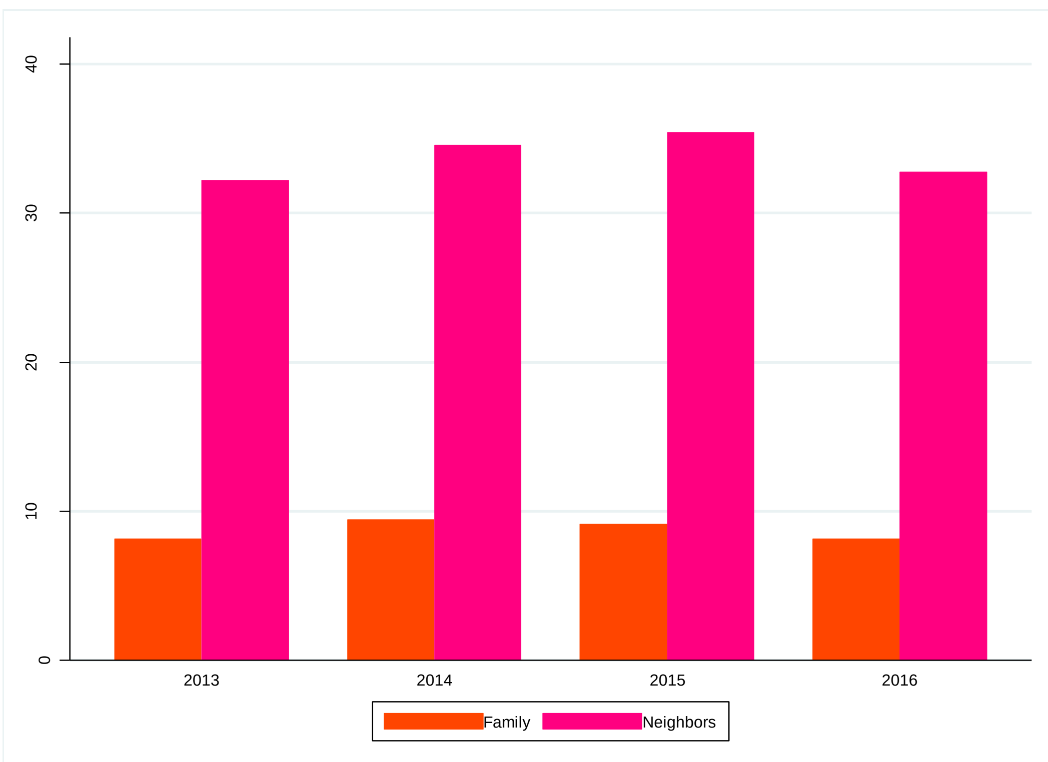
Predictive Margins with 95% confidence intervals. Further detailed in the Appendix.

Interpersonal Distrust

Socioeconomic background, individual victimization, neighborhood characteristics, and state and police presence are all factors that are significantly associated with levels of distrust in police forces, satisfaction with police performance, presence of self-help activities, perceptions of insecurity, and self-reported victimization. But are they also shaping the way people relate to others? More specifically, does crime increase the probability of an individual distrusting their family and neighbors?

Since 2013, ENVIPE collects information on whether Mexicans trust different members of the community. Figure 27 shows that for the past 4 years more than 30% of the population has reported to distrusting their neighbors and close to 10% has reported to distrusting their family. While distrust of family members has remained steadier across time, distrust of neighbors increased from 2013 to 2015 and went back to its original level by 2016.

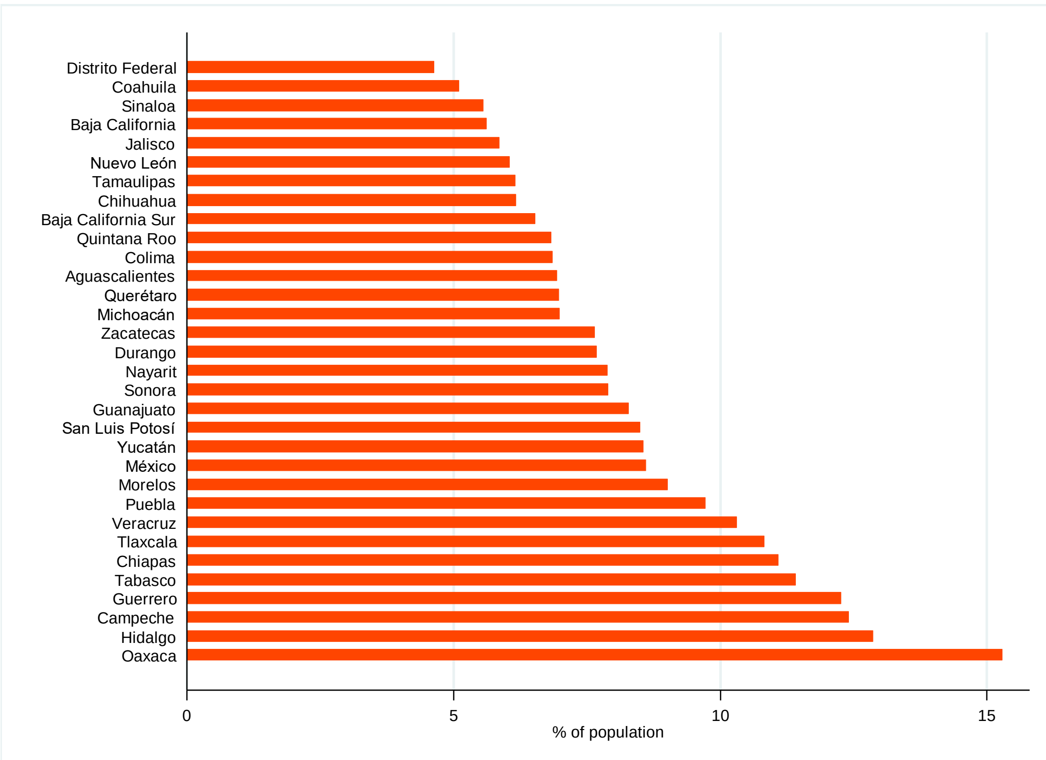
Figure 29. Interpersonal Distrust, % of population



Source: Stanford Poverty, Violence and Governance Lab with data from ENVIPE 2011-2016.

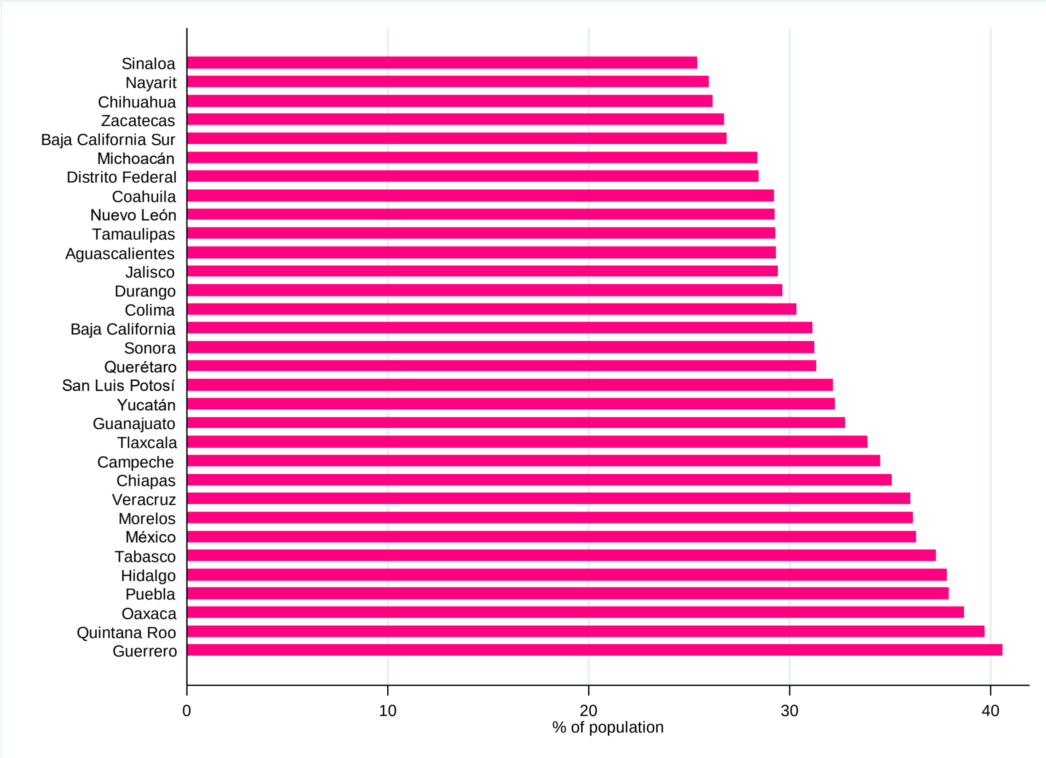
When analyzing how these levels of distrusts varied across states in 2016, we find that the states that consistently ranked as the most insecure or with the least trusted police officers are not necessarily the ones with the highest levels of interpersonal distrust. Although Distrito Federal has experienced high levels of crime and high levels of distrust and dissatisfaction with local police, it is the state that has the lowest percentage of its population distrusting family members (Figure 28). It also presents a low percentage in the neighbors' figure (Figure 29). In the case of distrust of neighbors, Sinaloa shows the lowest levels accompanied by Nayarit and Chihuahua.

Figure 30. Distrust of Family by State, 2016



Source: Stanford Poverty, Violence and Governance Lab with data from ENVIPE 2011-2016.

Figure 31. Distrust of Neighbors by State, 2016



Source: Stanford Poverty, Violence and Governance Lab with data from ENVIPE 2011-2016.

Following the analysis presented in the previous sections, we also performed an econometric examination of how sociodemographic characteristics, individual victimization, neighborhood features, and state and police presence and their relationship with citizen distrust of family and neighbors.

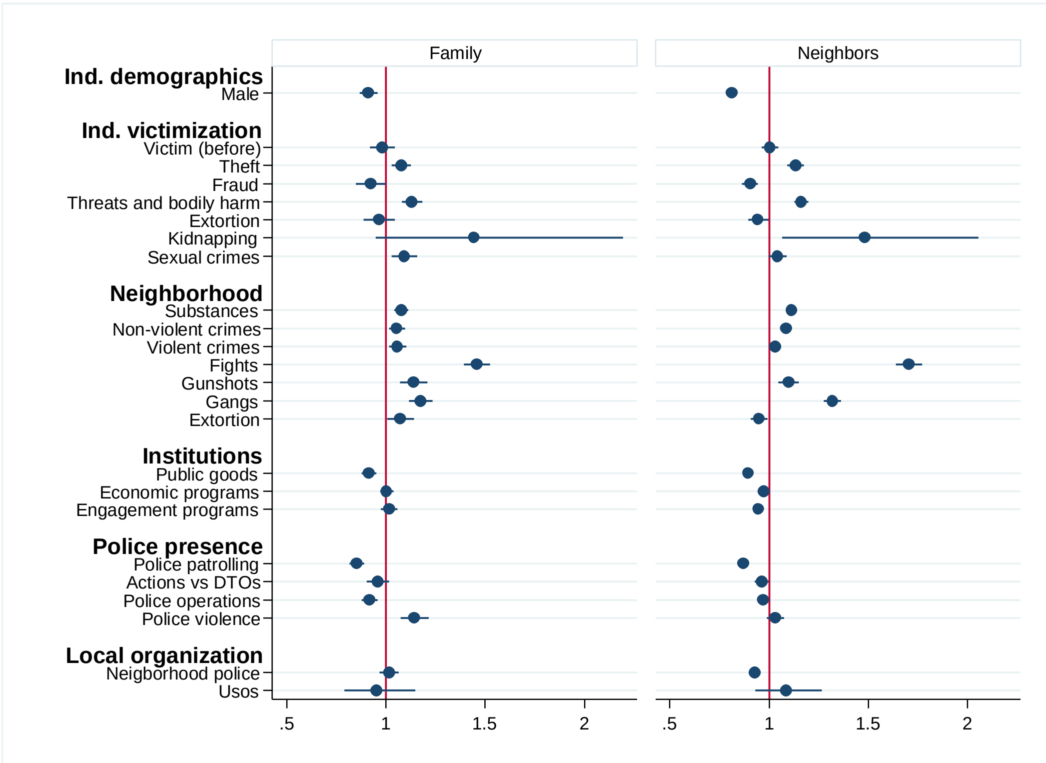
Figure 30 shows the estimates for both logistic models. Unlike previous sections, where individuals' victimization was associated with increases in the probabilities of feeling insecure, self-helping, and reported dissatisfaction with police performance, in this case, some crimes decreased the probability of distrusting and some other crimes that were not significant before became significant. For example, in the case of distrust of neighbors, being the victim of extortion or fraud is associated with decreases in the probability of distrusting, and being the victim of a sexual crime that was only significant for distrust of the army, became significant and positive for distrust of both family members and neighbors. These correlations suggest that some crimes are associated with crime perceptions and police performance, while some depend more on interactions within the community. While theft and extortion have a high correlation with distrust of local police forces and crime perceptions, victims of sexual crimes are more likely to distrust community members than non-victims.

In terms of the importance of neighborhood characteristics, associations are significant and positive. Specifically, if the individual perceives that there are fights between neighbors in the neighborhood, there is a high chance of distrusting both family and neighbors. However, the presence of extortion in the neighborhood does not follow this trend. When there is extortion in the neighborhood, individuals are less likely to distrust neighbors, which might suggest that extortion is not being committed by individuals from the community.

Another difference between these models of interpersonal distrust and those of crime perceptions and police satisfaction is the small impact of public goods and programs on the probability of distrusting. Even though coefficients show that state and police presences decrease the probability of distrusting, they do not seem to be the most effective strategy for strengthening community and family ties. Nonetheless, the model is consistent with the negative effect of police patrolling on distrust and the positive effect of police violence on the same variables.

In terms of local organization, individuals living in a neighborhood where people have organized to create a neighborhood or private police are less likely to distrust neighbors. In addition, individuals living in municipalities of Usos y Costumbres do not show a significant difference in levels of distrust of neighbors or family in comparison to individuals in regular municipalities. This is interesting given that Oaxaca, the state with the largest amount of Usos y Costumbres municipalities, presented some of the highest levels of interpersonal distrust in 2016.

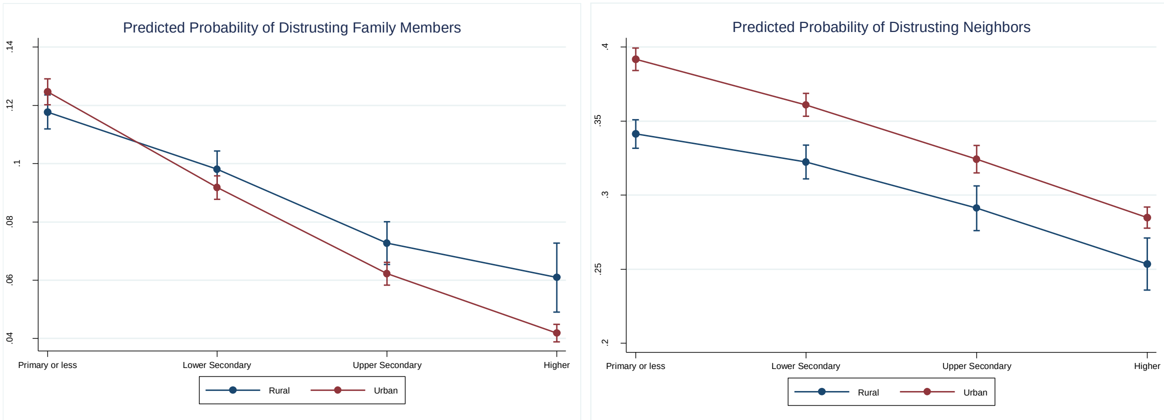
Figure 32. Estimated Effect Sizes of Distrust of Family and Neighbors



Note: Logit models with state and year FE and the interaction of both terms. 95% confidence intervals. Clustered standard errors by municipality. Observations weighted by survey weights. Models are also controlled for age, employment status, and family size. Further details of the estimation in the Appendix.

Concerning differences in the probability of interpersonal distrust across socioeconomic groups, Figure 31 details two of the clearest examples of the effect of years of education on individual perceptions. In previous sections, we suggested that educational attainment was associated with increases in the probabilities of feeling insecure and reports of crime victimization. However, the distrust of police models suggested the opposite relationship and the interpersonal distrust model graphs confirmed it: for both distrust of family members and neighbors, individuals with more years of schooling are less likely to distrust community members than the least educated ones. In the case of distrust of family, differences between urban and rural communities are only significant between individuals with higher education, with urban individuals having a very small chance of distrusting their family. For distrust of neighbors, the difference between rural and urban localities is always significant, with the least educated urban individuals presenting the highest chances of distrusting neighbors.

Figure 33. Predicted Probabilities of Distrust of Family and Neighbors by Socioeconomic Status



Predictive Margins with 95% confidence intervals. Further detailed in the Appendix.

Summary

This section of the report was focused on understanding how citizen satisfaction with police performance – in terms of its effectiveness, corruption, and trustworthiness – is determined and how it varies across socioeconomic groups, states, and time. When analyzing the changes in these perceptions over time, we find that, Mexicans have lower opinions of the most local police forces while finding the army and the navy to be highly trustworthy. For example, around 60% of the population considers that transit and municipal police are ineffective and more than 80% considers that the navy and the army are effective. Moreover, we find that these rates have remained roughly steady over time with slight decreases in recent years. Interestingly, in the case of perception of corruption, while perceptions of local police forces have not drastically changed, disapproval of the federal police, the navy and the army has been increasing since 2014.

This report draws from the idea that socioeconomic factors, neighborhood characteristics, state and police presence, and local forms of organization matter in the determination of citizen perceptions of police. Similar to the correlation showed for crime perceptions, in this part of the report we show that citizen satisfaction with police can be highly improved through increases in police presence – particularly, police patrolling – and, at the same time, can be highly affected by police violence. Furthermore, while in the previous section we could not find significant differences between perceptions of individuals living in Usos y Costumbres communities and individuals from regular municipalities, the logistic models of this part suggest that, in Usos communities, local police are around 50% less likely to be considered corrupt, ineffective, and untrustworthy than the local police in non-Usos settings.

When comparing distrust in municipal police and how much it has changed in the period between 2011 and 2016, we find that states are converging in their citizen distrust rates – i.e. states with high rates of distrust in 2011 have lowered these rates and states with low levels in 2011 are seeing increases in their distrust rates. Nonetheless, we show that the majority of states are decreasing their rates of distrust of police. This convergence is clearly seen in the case of Colima, which, in 2011, had the most trusted municipal police but by 2016, had experienced the highest increase in citizen distrust. In contrast, Nuevo Leon and Chihuahua, which had distrust rates above 70% in 2011, have decreased these percentages by more than 20 percentage points.

In the specific case of Nuevo Leon, its current levels of trust are similar to the ones of non-violent states like Yucatan and Nayarit.

When we compare individual distrust of all the police levels, we see that unlike the analysis of the perception of police ineffectiveness and corruption across socioeconomic groups, the probability of distrusting police appears to be lower when individuals have attained at least one year of higher education, relative to individuals with primary education or less. Overall, models of distrust of police and interpersonal distrust suggest that individuals with more years of schooling are less likely to distrust community members than individuals with lower educational attainment.

In addition, as we have shown throughout this report, individual victimization is a factor that is consistently associated with increases in the probabilities of disapproving of police performance. Nonetheless, we identify that crime is dynamic, with some crimes associating more with crime perceptions and police performance and some others depend more on the local social fabric or the social interactions within the community. Specifically, theft and extortion are highly correlated with distrust of local police forces and crime perceptions, while victims of sexual crimes are more likely to distrust community members than non-victims of sexual crimes.

III. Police Professionalization, Legitimacy, and Citizen Trust

Recognizing that citizen trust and police legitimacy are inextricably linked, the federal government of Mexico has launched a countrywide effort to reduce criminal violence and increase the public's trust in its police forces. The federal programs include police professionalization, state systems of unified command, reining in the emergence of militias and self-defense groups, and new training and technologies to curb excessive use of force. But from all we know, this national effort has delivered slow and wildly uneven results across different regions of the country. In this third part of the report, we focus on three federal practices intended to increase police legitimacy, professionalization, and effectiveness: Controles de Confianza (CC), changes in police size, and joint operations.

There is scant evidence of what works and what does not, and a similarly poor understanding of the institutional, social, and contextual dynamics that drive variations in effectiveness and levels of trust. The most explicit effort the Mexican government has taken to improve police legitimacy and citizen perception of police is the implementation of CC – "trust controls" – at the state, municipal and federal levels. CCs are evaluations intended to visibly demonstrate that police forces are trustworthy, competent, and honest. Specifically, CCs represented a federal effort in which all the states agree to implement five types of evaluations – toxicological and physiological exams, health and socioeconomic background checks, as well as polygraph tests – to all their police officers. The initiative was launched in 2010, after which, states had four years to create a local evaluation center and examine the totality of their police force. Evaluations are still performed periodically for existing members, and all new hires are subject to evaluation.

According to Secretariado Ejecutivo del Sistema Nacional de Seguridad Publica, by November 2016, 99% of all the police officers in the country had been evaluated, with 87% of those evaluated cleared (10% failing the evaluation and the other 2% pending results). In fact, by 2014, all states had evaluated at least 98% of their police force, with equal or higher rates in subsequent years. However, the pace at which states examined their officers was highly uneven. Through a transparency request, we obtained the progress of CC implementation in state and municipal forces from 2010 to 2015. As shown in Table 36, there were high variations between states and levels of police and across states and time. For example, by 2012, Aguascalientes, Coahuila, Distrito Federal and Sinaloa had almost finished evaluating their municipal police, while Baja California, Quintana Roo, San Luis Potosi, and Tabasco were more than 60 percentage points below the goal of evaluating every police officer.

Figure 36. Progress in the Implementation of Controles de Confianza, 2010-2016

State	2010		2011		2012		2013		2014		2015	
	State	Municipal	State	Municipal	State	Municipal	State	Municipal	State	Municipal	State	Municipal
Aguascalientes	15	38	80	81	86	100	100	88	100	100	99	100
Baja California	13	19	8	73	88	77	78	79	99	100	100	100
Baja California Sur	0	0	98	19	29	51	21	68	100	98	99	99
Campeche	0	0	38	14	95	92	99	100	100	100	100	100
Coahuila	19	38	64	64	97	99	91	94	100	100	100	100
Colima	21	21	78	54	91	96	100	100	100	100	100	100
Chiapas	1	20	25	26	84	82	89	78	100	96	99	100
Chihuahua	12	1	28	4	78	30	60	71	.	98	.	99
Distrito Federal	7	7	18	18	99	99	90	90	100	100	100	100
Durango	0	7	61	11	71	73	75	90	100	100	99	100
Guanajuato	21	24	81	66	76	94	99	97	100	99	100	100
Guerrero	10	3	14	14	52	86	51	64	100	100	99	97
Hidalgo	0	0	58	3	97	82	97	97	100	100	100	100
Jalisco	1	0	4	4	37	39	55	76	100	99	99	99
México	1	4	2	11	45	44	36	84	100	100	100	100
Michoacán	22	7	28	20	62	90	58	90	99	98	100	97
Morelos	4	37	27	48	92	98	78	83	100	100	100	100
Nayarit	0	0	29	1	71	42	83	93	100	100	100	100
Nuevo León	25	24	69	57	78	95	93	89	100	97	99	99
Oaxaca	8	2	16	20	35	66	98	99	99	100	99	100
Puebla	3	17	19	34	66	98	96	98	100	100	100	100
Querétaro	0	30	0	60	90	85	86	91	100	99	99	100
Quintana Roo	0	0	0	0	30	9	55	82	100	99	99	100
San Luis Potosí	1	0	5	7	34	40	76	92	100	100	100	100
Sinaloa	6	12	53	33	80	100	94	96	100	100	100	100
Sonora	18	1	58	24	42	82	95	95	100	100	100	100
Tabasco	1	9	25	12	26	67	91	98	100	100	100	100
Tamaulipas	10	0	30	4	53	16	94	24	100	100	100	100
Tlaxcala	32	6	85	16	87	76	96	90	100	100	100	99
Veracruz	2	4	18	9	84	34	91	71	100	100	100	100
Yucatán	24	4	23	9	93	33	98	88	100	100	100	99
Zacatecas	15	5	65	38	83	86	98	95	100	100	100	100

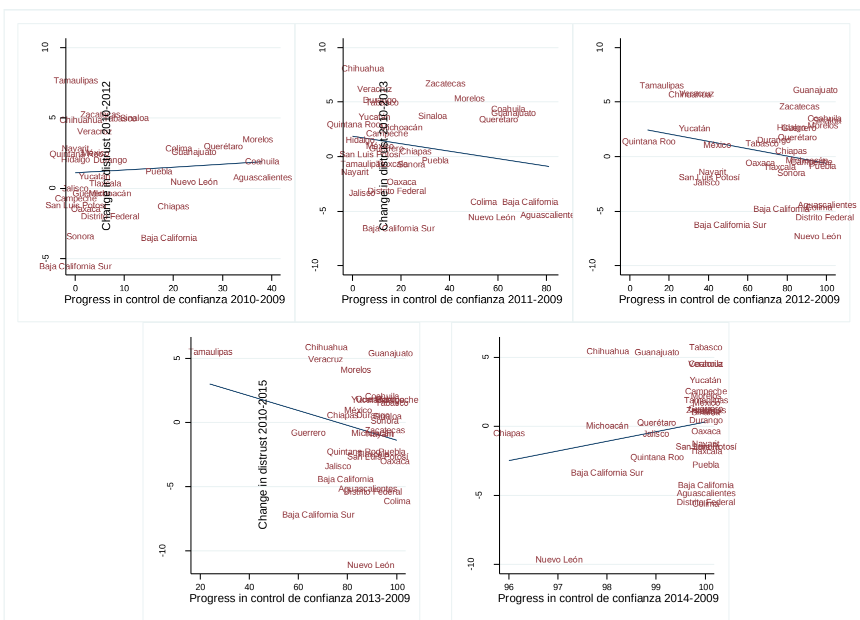
Source: Secretariado Ejecutivo del Sistema Nacional de Seguridad Pública (2016).

Do variations in the implementation of CCs across states explain their differences in citizen distrusts of police? Are CCs an effective tool for improving police legitimacy? To our knowledge, there is little existing research studying the impact of CCs on citizen's perceptions of police. Therefore, we address these questions by performing an econometric analysis to look at how different individual, neighborhood, state, and time trends associate with distrust levels.

This analysis follows from the three hypotheses that have guided this report. First, individual specific characteristics and victimization experiences can explain differences distrust levels across individuals. Second, individuals living in dangerous neighborhoods are more likely to distrust police – we believe that low levels of police legitimacy are associated with violent settings. Third, state presence and police presence – public goods provision, police patrolling, and actions against Drug Trafficking Organizations (DTOs) – are effective at increasing trust.

As a first approximation, Figure 37 shows the correlations between states' progress in the evaluations of municipal police and changes in states' distrust of municipal police. Both measures are relative to pre-treatment years: 2009, for CC implementation, and 2010, for distrust. We assume that progress in each year is reflected in states' distrust levels in the following year. In this exercise, if CC implementation had correlated with a drop in distrust, we would have observed a line with a negative slope. However, the direction of the slope is not constant across years and, in 2015, the slope is in fact positive, showing that changes in CC have not had a clear effect on changes in distrust of municipal police.[9]

Figure 37. Changes in the progress in the implementation of Controles de Confianza and changes in citizen distrust in municipal police, 2010-2015



Source: Stanford Poverty, Violence and Governance Lab with data from ENSI (2010), ENVIPE (2011-2015), and Secretariado Ejecutivo del Sistema Nacional de Seguridad Pública (2016).

[9] The lack of correlation is also present in the comparison of CC progress with citizen distrust in state police.

Following the econometric analysis performed in the first two parts of the report, we also measured whether CC implementation is associated with changes in citizen distrust across states and time. For this purpose, we propose two lineal regression models using individual level data from ENVIPE (2011–2016) and ENSI (2010). Unlike previous sections, in this analysis we are using pre-CC information from 2010 that does not allow us to run logistic models. [10] The first model focuses on distrust of municipal police forces, while the second looks at distrust of state police forces. The models control for the three hypothesis the report has been following – individual characteristics, neighborhood deterioration, and institutional presence and organization – and for state and year fixed effects for within-state comparisons. Because in the second of part of the report we thoroughly analyzed all the predictors of citizen distrust, in this section, we mainly focus on the effect of CCs and do not detail predictions across individual characteristics.

Figures 38 and 39 show the estimation of the effect of each variable. The model for individual distrust of municipal police (Figure 38) confirms that progress in the implementation of CC does not associate with changes in distrust levels. In other words, individuals with low levels of distrust are not necessarily the individuals that live in states that implemented CCs the quickest. Nevertheless, the analysis – that differs in the functional form and in the analyzed period from those of the first two parts of the report – confirms our previously described findings: individual demographics matter and individual victimization is an important factor associated with high levels of distrust. The model shows that being a victim of most crimes any year before the survey was collected is associated with higher levels of distrust. Furthermore, the estimation indicates that the quality of the neighborhood is an important predictor.

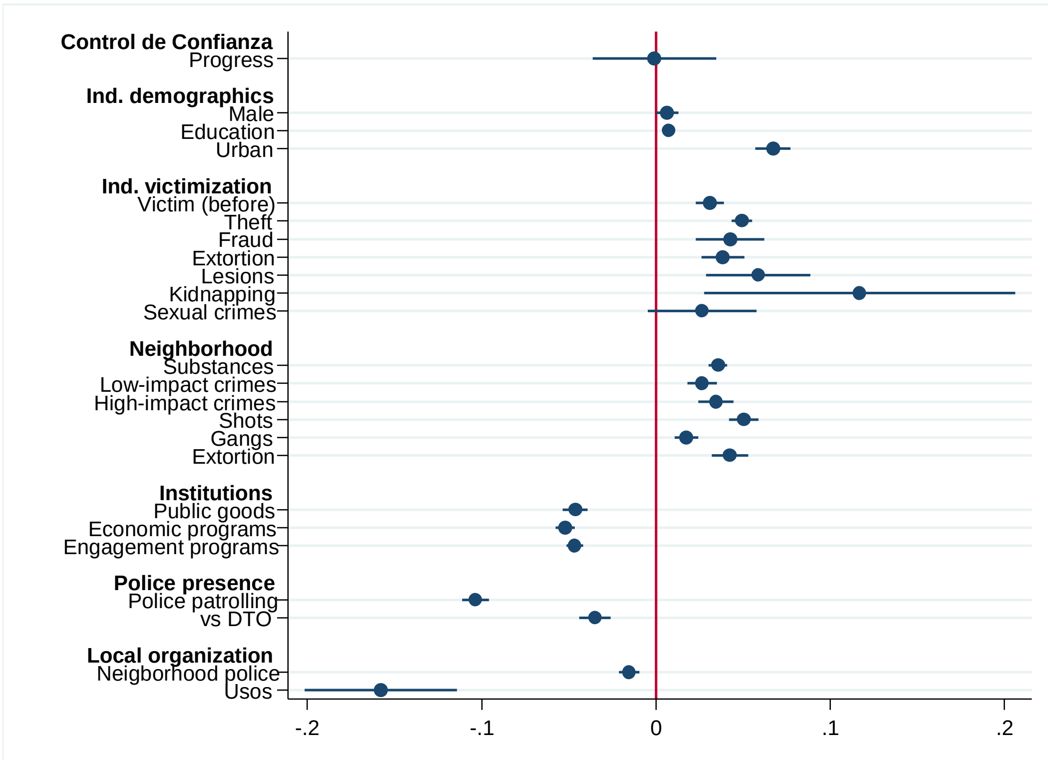
More importantly, we confirm that communities with Usos y Costumbres show the biggest gains in the model, suggesting that these police officers are organized in a way that can greatly increase their legitimacy within their community. Furthermore, the estimated coefficients for police presence are large. This relationship allows us to argue that police patrolling and actions

[10] ENSI and ENVIPE follow similar survey designs and, at least in the variables we considered for the models, both surveys are highly comparable. Nevertheless, given the way in which ENSI collected information of distrust, we had to modify ENVIPE data. One of the main differences between the two surveys is that ENSI used a 1-3 scale when evaluating distrust, while ENVIPE scale goes from 1 to 4. In order to estimate probabilities, in previous sections, we grouped perceptions of ineffectiveness and distrust in a 1-0 scale which allowed us to use logistic regressions. For these cases, we kept ENSI 1-3 design.

against DTOs are associated with low levels of distrust of municipal police. Police patrols are particularly noteworthy, having one of the biggest effect sizes in the model.

Figure 38. Estimated Effect Sizes of Predictors of Distrust of Municipal Police

Control de Confianza



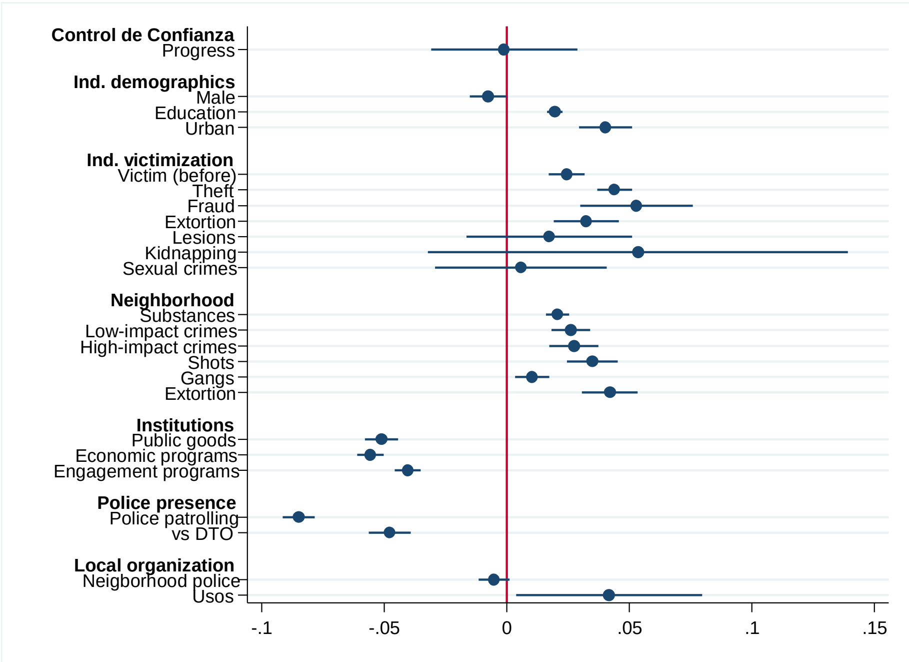
Note: OLS model with state and year FE. 95% confidence intervals. Clustered standard errors by municipality. Observations weighted by survey weights. Models are also controlled for age, employment status, and family size. Further details of the estimation in the Appendix.

Similar to the model of distrust of municipal police, the model of distrust of state police (Figure 39) shows that sociodemographic characteristics and victimization experiences matter when understanding citizen trust. The model also suggests that high-crime neighborhoods are more likely to have high levels of distrust than low-crime neighborhoods. Although CC implementation seems to have no impact on distrust of state police, we find that institutional policies and police presence could be an effective way to increase police legitimacy.

It is important to note that, unlike distrust of municipal police, living in areas with community police forces has no statistically impact on the public's trust of state police. More surprisingly, living in a community with Usos y Costumbres is actually associated with an *increase* in distrust of state police, which highlights how different is the perception of Usos y Costumbres police from regular forms of police such as state forces.

Figure 39. Estimated Effect Sizes of Predictors of Distrust of State Police

Control de Confianza



Note: OLS model with state and year FE. 95% confidence intervals. Clustered standard errors by municipality. Observations weighted by survey weights. Models are also controlled for age, employment status, and family size. Further details of the estimation in the Appendix.

Municipal and State Police Officer per Capita

The analysis of Controles de Confianza suggests that evaluating police officers does not seem to be an effective way to improve police legitimacy at the state or municipal level. Specifically, we could not find evidence that differences in distrust levels across states are correlated with differences in the implementation of CC. Nonetheless, we did find suggestive evidence that individuals living in neighborhoods where there are regular police patrols and public actions against DTOs, have lower levels of distrust than people living in neighborhoods that do not have these activities. With the importance of police presence in mind, in this section we measure the relationship between the number of police officers per inhabitant and citizen distrust of police.

In Table 40, we show the number of municipal and state police officers – in absolute levels – for each year and state. This information was obtained through a transparency request that provided information on CC evaluations and the universe of municipal and state officers that had been evaluated each year sin 2010. Overall, the table shows that states typically have more municipal police officers than state police officers, with the exceptions of Campeche, Mexico, Nayarit, Puebla, Oaxaca, San Luis Potosi, Tabasco, Tamaulipas, Tlaxcala, Veracruz, and Yucatan. In these cases, either the state police force was always bigger than the municipal one or, over time, the number of municipal police officers decreased while the size of the state force remained relatively constant. For the rest of the states, the ratio of state police officers to municipal police officers remained the same, although they also follow the trend of a decreasing municipal police. The only case in which the size of the state police considerably decreased – to the point of disappearing – is the state police of Chihuahua. We assume that in Chihuahua, the state police force disappeared in 2013, as there were no state police officers subject to CC evaluations.

Figure 40. Universe of Active Municipal and State Officers by State, 2010-2015

State	2010		2011		2012		2013		2014		2015	
	State	Municipal	State	Municipal	State	Municipal	State	Municipal	State	Municipal	State	Municipal
Aguascalientes	524	2244	456	1996	485	2416	622	2603	458	2094	516	2138
Baja California	1068	6,292	6205	2,204	1984	6,832	1466	7,647	783	6,051	885	5,930
Baja California Sur	258	2387	81	2134	302	2319	513	2449	235	2106	255	2037
Campeche	1009	853	1006	843	1220	893	1361	792	1186	705	1167	687
Coahuila	686	3,647	1664	3,714	1394	4,908	1585	2,987	1426	2,823	1562	2,917
Colima	708	1351	725	1273	802	1339	953	1202	825	1074	783	1080
Chiapas	4438	7,187	4614	8,866	3816	6,693	8561	9,037	6840	7,906	5838	5,702
Chihuahua	1177	7258	1339	6754	1819	6739	10	7090	.	6285	.	6436
Distrito Federal	83,973	83973	83,973	83973	88,074	88074	89,583	89583	36,221	36221	36,709	36709
Durango	539	2688	460	2901	725	2611	946	1933	901	1523	931	1634
Guanajuato	1,364	9,360	1,591	9,240	2,637	11,172	1,645	8,883	1,382	7,551	1,958	7,685
Guerrero	5140	7838	5140	7838	3584	5307	5976	7097	2839	4960	3015	4756
Hidalgo	3069	4225	3534	4212	3572	5041	3839	4270	3162	3937	2613	3560
Jalisco	5532	14557	5410	14557	5186	13539	6654	13731	4132	11608	4649	11293
México	38,468	24,894	38,468	24,894	25,015	22,782	44,464	25,137	18,172	22,908	17,710	22,840
Michoacán	3,117	6113	3,117	6113	3,631	4622	4,273	5621	1,903	4306	1,779	4152
Morelos	1738	3,651	1738	3,651	1970	3,917	2329	4,206	1352	3,463	1448	3,253
Nayarit	346	1865	1229	1135	1436	2394	1718	2151	1191	1778	1319	1654
Nuevo León	2195	6,664	2195	6,664	2865	7,542	4864	6,865	4673	6,613	4832	6,626
Oaxaca	6009	4688	7181	4688	6387	4585	6300	3010	3526	2516	3612	2487
Puebla	6712	6,460	6712	6,460	4424	5,962	8095	6,436	3518	4,612	3782	5,132
Querétaro	720	2357	720	2357	751	2738	802	3077	866	2935	874	2916
Quintana Roo	1060	3528	1165	4155	1610	4582	1620	4353	1202	4075	1195	3806
San Luis Potosí	3850	3389	3850	3389	4621	3558	4141	3601	3070	3172	3805	2818
Sinaloa	1303	6144	1399	5432	1084	5450	2257	5953	1965	5161	1694	4888
Sonora	417	4912	535	5794	1645	6076	1590	5885	1358	3100	1247	3828
Tabasco	4025	4296	3986	4407	5008	3933	5119	3814	3710	3966	4369	4134
Tamaulipas	1409	5457	1406	5268	1855	3729	2792	2891	2985	500	3118	498
Tlaxcala	1977	1803	1977	1803	2859	1935	1787	1514	1368	944	1260	1119
Veracruz	11651	5913	9805	8345	13587	5701	14059	5105	6394	3714	6545	2902
Yucatán	3075	3465	3865	3465	3654	3203	3520	2717	3108	2677	3095	2433
Zacatecas	485	2301	691	2325	972	2766	1221	2046	1056	1147	1138	1215

Source: Secretariado Ejecutivo del Sistema Nacional de Seguridad Pública (2016).

Although the variation in the size of state and municipal police could be explained by changes in political administrations, renewal of police forces due to CC or the creation of new police teams, states seem to be decreasing municipal police forces, while increasing state police forces. In Figure 41, we map the percentage change in the number of state and municipal police officers from 2010 to 2015. Increases in the rates are shown in green – with the states in the darkest green showing the highest increases – and decreases are shown in red – with the states in the darkest red showing the biggest decreases.

The fist map shows changes in state police. With the exception of Chihuahua, Michoacán, Guerrero, Oaxaca, Veracruz, Puebla, Mexico, Distrito Federal, and Tlaxcala, states increase the size of their state police. Nayarit and Sonora present the biggest increases. In the second map, we mostly observe large declines: Nuevo Leon, Queretaro and Quintana Roo are the only states that increased their municipal police from 2010 to 2015 and Tamaulipas, Veracruz and Oaxaca considerably reduced it.

Figure 41. Percentage Change in Police Officer Per Capita Rates, 2010-2015

State police

Municipal police

Source: Stanford Poverty, Violence and Governance Lab with data from Secretariado Ejecutivo del Sistema Nacional de Seguridad Pública (2016).

Similar to our analysis of how CCs are associated with variation in distrust across states and time, we measure how the rates of municipal and state police officers per capita correlate with individual distrust of state and municipal police. We assume that the size of the rate in a given year impacts the next years' level of distrust. Because the first year of the information provided in the transparency request was 2010, we only use ENVIPE information. By only using ENVIPE data, we are able to use logistic models with a dependent variable that takes the value of one when the individual distrusts the police and the value of zero when the individual trusts the police. In terms of the rest of the variables, these models are identical to the CC analysis with the only differences being that the analyzed period is 2011-2016 and the variables of joint operations and police violence are added. We could not control for theses variables in the CC model because they were not available in ENSI 2010 (the CC pre-treatment year).

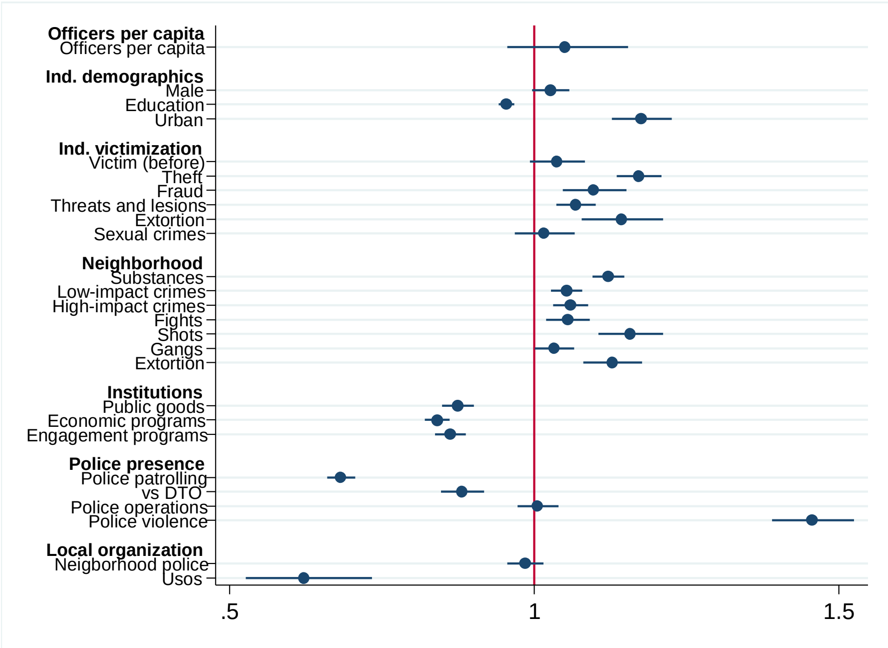
In Figures 42 and Figure 43, we show the estimation of the effect of each variable. To provide a more robust approximation of police presence, the rates of municipal and state officers per capita are standardized, indicating how each state compares to the national average, rather than showing its magnitude. Overall, both the municipal and state models show that the number of officers per capita does not provide a statistically significant prediction of distrust. Therefore, we cannot conclude that police presence, in terms of number of officers, is associated with an increase or decrease in citizen trust. However, the models do allow us to confirm some of the results of the CC analysis. First, males are more likely to distrust municipal police than females, but less likely to distrust state police than females. Also, individuals living in urban settings are more likely to distrust police than individuals living in rural settings. Second, being victim of a crime increases the likelihood of distrusting both state and municipal police.[11] Third, individuals living in high-crime neighborhoods are more likely to distrust both types of police than individuals living in less violent settings. Fourth, public programs and police presence are associated with declines in the probability of distrusting police. Fifth, individuals living in Usos y Costumbres communities are significantly less likely to distrust municipal police, but they are more likely to distrust state police than individuals living in regular municipalities.

[11] We do not include kidnapping in the figures for visualization purposes. For more details on the estimated effects of each variable, see Appendix.

The inclusion of two new variables related to police presence provides information that the CC models did not show. For both state and municipal police, the presence of police violence in the neighborhood highly increases the probability of distrusting police. The estimated effect for this variable is greater than that of police patrolling. For police operations, both models suggest that its effect is not significant for municipal distrust, and negative for state distrust. This means that when individuals live in neighborhoods where they can see police operations, they are less likely to distrust state police.

Figure 42. Estimated Effect Sizes of Predictors of Distrust of Municipal Police

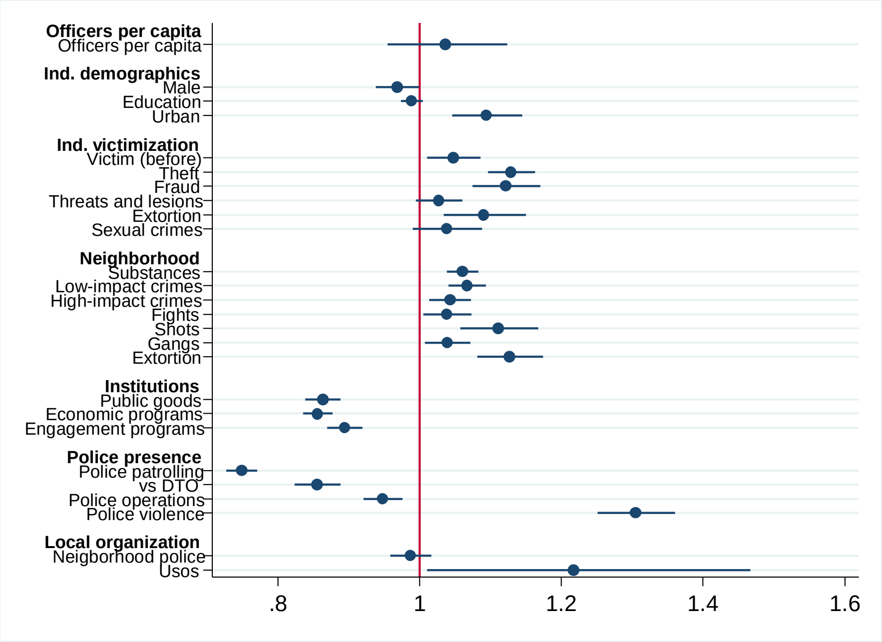
Officers per capita



Note: OLS model with state and year FE. 95% confidence intervals. Clustered standard errors by municipality. Observations weighted by survey weights. Models are also controlled for age, employment status, and family size. Further details of the estimation in the Appendix.

Figure 43. Estimated Effect Sizes of Predictors of Distrust of State Police

Officers per capita



Note: OLS model with state and year FE. 95% confidence intervals. Clustered standard errors by municipality. Observations weighted by survey weights. Models are also controlled for age, employment status, and family size. Further details of the estimation in the Appendix.

Joint Operations

The previous sections provided evidence suggesting that increases in police presence – through police patrols, actions against DTOs, and police operations – could be an effective way to increase citizen trust in municipal and state police. Therefore, the third governmental effort we analyze in this report is the association between joint operations (i.e. the police operations in which local and federal forces work together to combat DTOs) and citizen distrust of all the police levels that participate in these operations. Most of the information on joint operations is classified by the government. Nonetheless, our partnership with Comision Nacional de Seguridad allowed us to identify five states where the federal government, in collaboration with local authorities, implemented joint operations in 2014. These states are Tamaulipas, Guerrero, Michoacan, Mexico and Morelos and are shown in red in the following map (Figure 44).

Figure 44. States where Joint Operations were Implemented, 2014

Source: Stanford Poverty, Violence and Governance Lab with data from Comision Nacional de Seguridad (2014).

Although one year of data is not enough to provide a robust model, and it certainly is possible that the previously mentioned states were not the only ones who experienced joint operations in 2014, we still believe it is useful to measure whether the predictors we have been analyzing throughout the report vary when analyzing this specific police intervention. Our objectives are threefold. First, identify how joint operations in 2014 associate with distrust levels in 2015. Second, analyze this correlation across different levels of police, including local and federal authorities. And third, provide more evidence on how individual experiences, neighborhood deterioration, local organization, institutional programs, and police presence associate with police legitimacy.

Figures 45, 46 and 47 show the estimates of five logistic models in which individual distrust of municipal, state and federal police, the navy, and army are explained by joint operations and the covariates we used in previous sections.[12] The models show that there is no significant correlation between joint operations and individual distrust of all levels of police, except for distrust of state police. However, because of the nature of this analysis and the limited available data, we cannot arge that joint operations directly increased the probability of distrusting state police. Nevertheless, the magnitude of the estimate does suggest that perceptions of municipal and federal police and perceptions of the army and the navy were not necessarily affected in the same way by joint operations as perceptions of state police.

In terms of the other variables, the models confirm that males are more likely to trust the authorities that are less proximate to them. Men trust the state, federal, and military authorities more than women, with the biggest differences between genders present in the army and navy models. In addition, differences between distrusts of rural and urban individuals decrease as the distance between the citizen and the officer grows – for example, there are no significant differences in the case of distrust of the navy.

Regarding victimization, the models confirm that being a victim of a crime increases the probability of distrusting police, particularly municipal and state police – the estimated effects of victimization on federal forces are not significant overall. Nevertheless, the models show some relationships that deserve further analysis. First, prior victimization is associated with increased trust in navy while suffering a sexual crime has a positive correlation with distrust in the army. These effects are not observed in the rest of the models, which might indicate that distrust is not affected by all forms of victimization identically.

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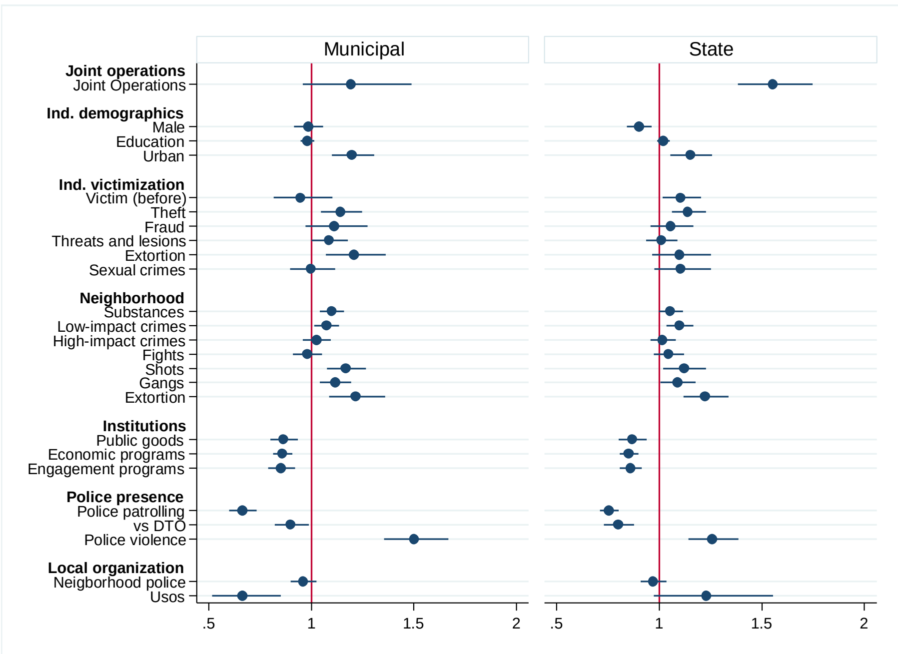
[12] For visualization purposes, kidnapping was not included. More details on the specific estimations are included in the Appendix.

The estimates of neighborhood quality, institutional programs, police presence, and local organization are consistent to what we showed in the previous sections. Similarly, police presence is associated with a reduction in distrust, while police violence is always significantly correlated with a higher distrust, with police violence's biggest effect present in municipal model. Finally, individuals living in Usos y Costumbres communities do not seem to distrust police in the same way as individual living in regular communities. The models suggest that they are less likely to distrust municipal police and more likely to distrust federal police and the army – relative to individuals living in non-Usos y Costumbres communities.

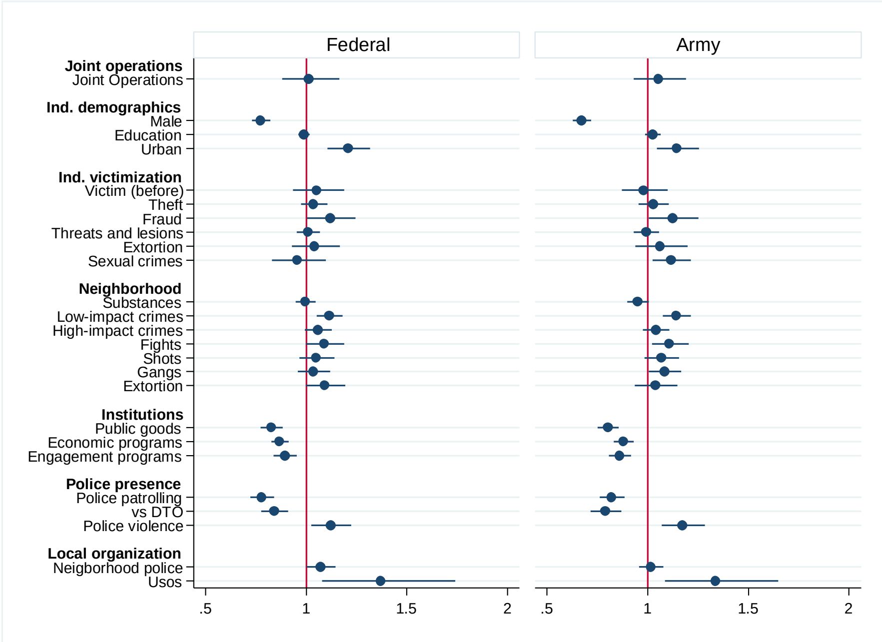
Figure 45. Estimated Effect Sizes of Predictors of Distrust of Municipal and State Police

Joint Operations



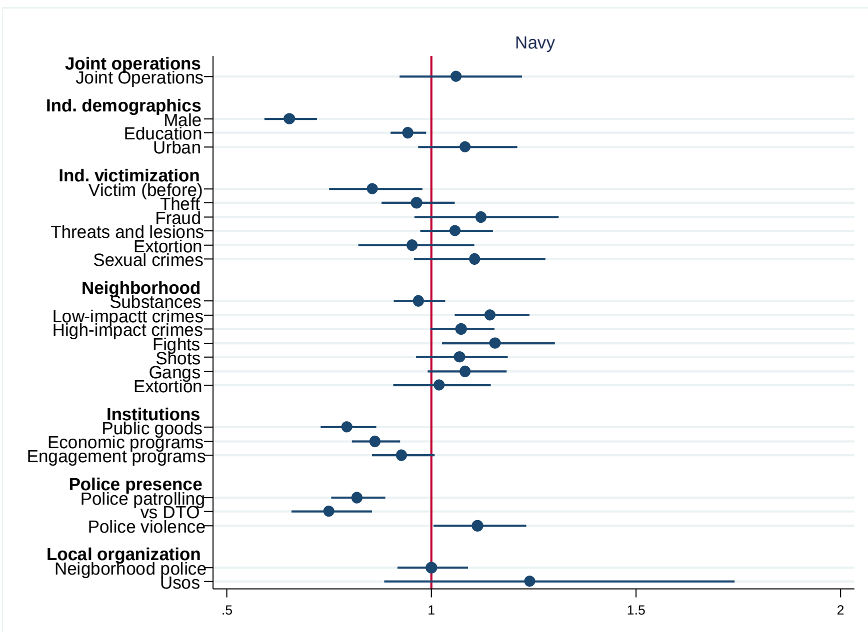
Note: OLS model with state and year FE. 95% confidence intervals. Clustered standard errors by municipality. Observations weighted by survey weights. Models are also controlled for age, employment status, and family size. Further details of the estimation in the Appendix.

Figure 46. Estimated Effect Sizes of Predictors of Distrust of Federal Police and Army: Joint Operations



Note: OLS model with state and year FE. 95% confidence intervals. Clustered standard errors by municipality. Observations weighted by survey weights. Models are also controlled for age, employment status, and family size. Further details of the estimation in the Appendix.

Figure 47. Estimated Effect Sizes of Predictors of Distrust of Navy: Joint Operations



Note: OLS model with state and year FE. 95% confidence intervals. Clustered standard errors by municipality. Observations weighted by survey weights. Models are also controlled for age, employment status, and family size. Further details of the estimation in the Appendix.

Summary

In this third part of the report, we focus on three federal practices intended to increase police legitimacy and professionalization. We specifically aim to understand whether variations in citizen distrust levels across states are related to variations in the implementation of these practices by state authorities.

Our descriptive and statistical analyses of Controles de Confianza, rates of police officers per capita, and joint operations allow us to conclude the following. First, regarding CCs, while there was a large variation in how the CC program was implemented at the state and municipal level, we could not find evidence to argue that this variation explains the differences in trust levels among the states. However, the econometric analysis supports our hypotheses of how distrust is determined. Evidence suggests that sociodemographic characteristics and experience being a victim of a crime explain differences across citizens, with distrust of municipal police being more affected by victimization than distrust of state police. Moreover, the models suggest that people living in low-crime neighborhoods as well as those living in neighborhoods where there is greater police presence and public goods provision are less likely to distrust state and municipal police. In addition, while police patrolling and police actions against DTOs seem to be an effective way to grow trust, police violence can have a negative impact on trust. Finally, this analysis shows that local organizations matter. Individuals living in Usos y Costumbres communities are less likely to distrust their local police than individuals living in regular communities.

Second, regarding the question of whether police presence – understood as number of police officers per capita – can affect citizen distrust, our descriptive approach demonstrates that there is a clear national trend in which the majority of states are reducing their municipal police forces while increasing their state ones. Regardless of this general decrease, we could not find evidence showing that variations across states in per capita rates are associated with variations in citizen distrust of municipal and state police. Nevertheless, the analysis, which differed in the analyzed period and the functional form of the model from the CC analysis, confirms the pertinence of our proposed predictors. Furthermore, this evidence allows us to argue that police patrolling, police actions against DTOs, and police operations can significantly affect distrust of police.

Following the importance of police presence, in the third section, we specifically analyze the effect of the joint operations implemented in five different states in 2014 on 2015 individual levels of distrust. Although this analysis is not as robust as the others given the lack of data, analyzing joint operations allows us to confirm, again, the importance of individual characteristics and experiences, neighborhood characteristics, institutional and police presence, and local forms of organization on the amount of distrust in police. Moreover, the models in this section show that distrust of different levels of police are not affected in the same way by the proposed covariates. For example, distrust of municipal police is more affected by individual victimization and local forms of organization than the other levels of police – with the exception of victims of sexual crimes that are more likely, than non-victims of this kind of crime, to distrust the army.

Overall, we believe to have provided enough evidence to argue that the implementation of Controles de Confianza, variations in officers' per capita, and joint operations are not the most effective practices in terms of improving police legitimacy. Nonetheless, the descriptive and econometric approaches of this report provide evidence on how some states appear to be more successful than others in increasing citizen trust in police. We also find that other factors hold a higher correlation with individual distrust than the three analyzed governmental interventions. We encourage police professionalization efforts to focus on increasing municipal police patrolling – and decreasing police violence – and to complement this effort with the provision of public goods and economic and engagement programs. Furthermore, we consider that citizen cooperation with local police forces in communities ruled by Usos y Costumbres represents a successful alternative in terms of improving police legitimacy in small, rural and indigenous communities.

Methodological Note

1. All the calculations– graphs, tables, maps, and models – were weighted by ENVIPE's survey weights that are based on Mexico's population aged 18 years or older (fac_ele and fac_ele_am).
2. Victimization, as a dependent variable, is a dichotomous indicator that takes the value of one when the individual reports to have suffered any kind of crime in the year before the survey was collected – all the crimes, which vary across ENVIPE editions, were considered. It also takes the value of one when the individual's family suffered house theft, partial and total car theft or a family member was kidnapped, disappeared or murdered. The indicator takes the value of zero in any other case.
3. In the case of Distrito Federal, perceptions of municipal police are identical to perception of state police.
4. Measures of distrust and ineffectiveness for the period 2011-2016 were modified to fit a 0-1 scale (0= trust and 1=distrust: 0=effective and 1=ineffective). Originally, the survey collects the information in a 1-4 scale, so we grouped options 1 and 2 to create the lowest disapproval and options 3 and 4 to create the highest disapproval.
5. Measures of distrust for the period 2010-2016 were modified to fit a 1-3 scale, which is the scale used by ENSI 2010. Options 2 and 3 from ENVIPE were grouped in a category with the value of "2".
6. Educations levels are defined as follows: Primary or less includes individuals that attained at least one year of primary or preschool. Lower secondary includes individuals that attained at least one year of lower secondary education. Upper secondary includes individuals that attained at least one year of upper secondary education. Higher includes individuals that attained at least one year of teachers college, technical careers, and ungraduated and graduate studies.
7. ENVIPE classifies localities in three ways: urban, semi urban, and rural. In this analysis, we considered urban and semi-urban as urban.
8. Indicators that include more than one variable were calculated with a principal factor analysis. All the models in the first two parts of the report are run with an interaction of state and year fixed-effects and with clustered standard errors by municipality. Models of

the third part do not include fixed-effects interactions, nor sociodemographic interactions. Estimations for the logistic models are presented in odds ratios.

9. The variables in the logistic models were defined or created as follows:

Logistic models with ENVIPE 2011-2016

Individual victimization	**Definition / factors**
Victim (before)	Victim of a crime any time before the survey was collected.
Theft	House theft (family), Partial and total car theft (family), Street theft, Other kinds of theft
Fraud	Consumer fraud, Banking fraud
Threats and bodily harm	Threats, Bodily harm
Extortion	Extortion
Kidnapping	Kidnapping
Sexual crimes	Sexual harassment, Rape

Neighborhood characteristics (individual perception on the neighborhood)	
Substances	Drug consumption, Drug distribution, Alcohol consumption, Alcohol distribution
Non-violent crimes	Land invasion, Prostitution, Bootleg, Thefts
Violent crimes	Kidnapping, Homicides
Fights	Fights between neighbors
Gunshots	Gunshots
Gangs	Gangs
Extortion	Extortion

Institutional development (individual perception on the municipality)	
Public goods	Courts and parks, Public Lighting
Economic programs	Income programs, Unemployment programs
Engagement Programs	Gang prevention programs, Engagement programs, Anticorruption programs
Patrolling	Police patrolling
vs DTO	Operations against Drug Trafficking Organization
Operations	Police operations
Police violence	Police violence

Linear models with ENSI 2010 and ENVIPE 2011-2016

Individual victimization	**Definition / factors**
Victim (before)	Victim of a crime any time before the survey was collected.
Theft	House theft (family), Partial and total car theft (family), Street theft, Other kinds of theft
Fraud	Consumer fraud, banking fraud

Wounds	Wounds
Extortion	Extortion
Kidnapping	Kidnapping
Sexual crimes	Sexual harassment
Neighborhood characteristics (individual perception on the neighborhood)	
Substances	Drug consumption, Drug distribution, Alcohol consumption, Alcohol distribution
Low-impact crimes	Bootleg, Thefts
High-impact crimes	Kidnapping
Shots	Gun shots
Gangs	Gangs
Extortion	Extortion
Institutional development (individual perception on the municipality)	
Public goods	Public Lighting
Economic programs	Income programs, Unemployment programs
Engagement Programs	Gang prevention programs, Engagement programs, Anticorruption programs
Patrolling	Police patrolling
vs DTO	Operations against Drug Trafficking Organization
Neighborhood police	Neighbors organizing to hire private security, Neighbors organizing to create neighborhood police

Appendix

A1. Perception of Insecurity and Victimization

VARIABLES	Insecurity	Victimization	Victimization*
Individual demographics	**(odds ratio)**	**(odds ratio)**	**(odds ratio)**
Male	0.721***	1.078***	1.078***
	(0.00992)	(0.0148)	(0.0148)
Age	1.033***	1.005**	1.005***
	(0.00205)	(0.00187)	(0.00187)
Age2	1.000***	1.000***	1.000***
	(2.05e-05)	(1.99e-05)	(2.00e-05)
Family size	1.005	1.005	1.005
	(0.00385)	(0.00367)	(0.00365)
Employed	0.947***	1.074***	1.074***
	(0.0122)	(0.0151)	(0.0151)
Years of schooling and local context			
Lower secondary education	1.301***	1.434***	1.434***
	(0.0382)	(0.0488)	(0.0488)
Upper secondary education	1.309***	1.918***	1.913***
	(0.0550)	(0.0820)	(0.0820)
Higher education	1.364***	2.951***	2.939***
	(0.0729)	(0.181)	(0.180)
Lower secondary education*Urban	0.774***	0.990	0.987
	(0.0261)	(0.0378)	(0.0377)
Upper secondary education*Urban	0.747***	1.011	1.008
	(0.0331)	(0.0488)	(0.0487)
Higher education*Urban	0.693***	0.791***	0.787***
	(0.0407)	(0.0525)	(0.0523)
Urban	1.034	1.577***	1.567***
	(0.0308)	(0.0537)	(0.0531)
Local characteristics			
Deprivation index 2010	0.961*	0.710***	0.711***
	(0.0217)	(0.0174)	(0.0173)
Usos y Costumbres	1.188	1.201	1.201
	(0.130)	(0.133)	(0.134)
Individual victimization			
Victim (before)	1.098***	3.819***	3.810***
	(0.0203)	(0.101)	(0.101)
Theft	1.160***		
	(0.0186)		
Fraud	1.009		
	(0.0210)		
Threats and bodily harm	0.992		
	(0.0163)		
Extortion	1.189***		
	(0.0306)		
Kidnapping	1.397**		

	(0.211)		
Sexual crimes	0.995		
	(0.0218)		
Neighborhood characteristics			
Substances	1.185***	1.123***	1.122***
	(0.0142)	(0.0131)	(0.0132)
Non-violent crimes	1.109***	1.162***	1.160***
	(0.0181)	(0.0152)	(0.0151)
Violent crimes	1.178***	1.078***	1.079***
	(0.0163)	(0.0115)	(0.0115)
Fights	1.051***	1.093***	1.093***
	(0.0190)	(0.0182)	(0.0181)
Gunshots	1.223***	1.163***	1.162***
	(0.0258)	(0.0206)	(0.0205)
Gangs	1.187***	1.234***	1.234***
	(0.0190)	(0.0189)	(0.0189)
Extortion	1.181***	1.433***	1.431***
	(0.0281)	(0.0292)	(0.0292)
Institutional development			
Public goods	0.938***	1.031**	
	(0.0152)	(0.0152)	
Parks and courts			1.119***
			(0.0190)
Lighting			0.935***
			(0.0137)
Economic programs	0.886***	0.919***	0.923***
	(0.0113)	(0.0122)	(0.0121)
Engagement Programs	0.914***	1.070***	1.068***
	(0.0115)	(0.0143)	(0.0142)
Patrolling	0.897***	0.837***	0.841***
	(0.0122)	(0.0124)	(0.0124)
vs DTO	0.854***	0.977	0.978
	(0.0161)	(0.0181)	(0.0180)
Operations	1.055***	1.114***	1.112***
	(0.0160)	(0.0186)	(0.0186)
Police violence	1.091***	1.099***	1.099***
	(0.0213)	(0.0208)	(0.0207)
Neighborhood police	0.991	1.100***	1.101***
	(0.0139)	(0.0147)	(0.0147)
Constant	0.798*	0.0915***	0.0897***
	(0.109)	(0.00882)	(0.00860)
Year*State FE	Yes	Yes	Yes
Observations	408,806	445,232	445,232

Clustered standard errors by municipality.
Observations weighted by household weights.
*** p<0.01, ** p<0.05, * p<0.1

A2. Street and Car theft, Extortion, and Lesions

VARIABLES	Street Theft	Car Theft	Extortion	Lesions
Individual demographics	**(odds ratio)**	**(odds ratio)**	**(odds ratio)**	**(odds ratio)**
Male	1.171***	1.124***	0.911***	1.824***
	(0.0360)	(0.0423)	(0.0242)	(0.120)
Age	0.952***	1.022***	1.060***	0.947***
	(0.00391)	(0.00703)	(0.00411)	(0.00831)
Age2	1.000***	1.000***	1.000***	1.000**
	(4.59e-05)	(7.40e-05)	(4.25e-05)	(0.000105)
Family size	0.985**	1.089***	0.987*	1.010
	(0.00698)	(0.0117)	(0.00752)	(0.0142)
Employed	1.117***	1.076*	0.916***	1.057
	(0.0327)	(0.0418)	(0.0260)	(0.0870)
Years of schooling and local context				
Lower secondary education	1.199**	1.673***	2.071***	1.073
	(0.0996)	(0.275)	(0.144)	(0.140)
Upper secondary education	1.472***	1.846***	2.699***	1.049
	(0.140)	(0.333)	(0.238)	(0.167)
Higher education	2.134***	3.459***	3.511***	0.831
	(0.274)	(0.690)	(0.324)	(0.178)
Lower secondary education*Urban	0.999	0.882	0.610***	0.929
	(0.0894)	(0.154)	(0.0480)	(0.140)
Upper secondary education*Urban	0.877	1.057	0.604***	1.036
	(0.0862)	(0.198)	(0.0581)	(0.191)
Higher education*Urban	0.509***	0.650**	0.571***	0.909
	(0.0683)	(0.134)	(0.0578)	(0.210)
Urban	1.821***	1.755***	1.959***	1.184
	(0.130)	(0.203)	(0.119)	(0.144)
Local characteristics				
Deprivation index 2010	0.581***	0.556***	0.988	0.869***
	(0.0277)	(0.0325)	(0.0288)	(0.0425)
Usos y Costumbres	1.579***	1.441	0.941	1.379
	(0.236)	(0.465)	(0.136)	(0.362)
Individual victimization				
Victim (before)	5.304***	1.392***	3.902***	4.336***
	(0.204)	(0.0575)	(0.136)	(0.231)
Neighborhood characteristics				
Substances	1.128***	0.998	1.043**	1.171***

	(0.0260)	(0.0310)	(0.0198)	(0.0395)
Non-violent crimes	1.011	1.060*	0.997	1.015
	(0.0259)	(0.0325)	(0.0200)	(0.0443)
Violent crimes	1.041**	1.163***	1.086***	1.124**
	(0.0210)	(0.0409)	(0.0226)	(0.0530)
Fights	1.062*	0.917**	0.968	1.403***
	(0.0328)	(0.0394)	(0.0276)	(0.0809)
Gunshots	1.196***	1.050	1.078**	1.069
	(0.0376)	(0.0506)	(0.0326)	(0.0656)
Gangs	1.250***	1.113**	1.000	1.228***
	(0.0388)	(0.0521)	(0.0339)	(0.0748)
Extortion	1.085**	1.405***	2.144***	1.050
	(0.0400)	(0.0870)	(0.0779)	(0.0585)
Institutional development				
Public goods	1.031	0.949*	1.011	1.005
	(0.0284)	(0.0267)	(0.0229)	(0.0469)
Economic programs	0.994	0.905***	0.944***	0.974
	(0.0276)	(0.0334)	(0.0175)	(0.0436)
Engagement Programs	1.038*	1.066*	1.044**	1.106**
	(0.0217)	(0.0357)	(0.0224)	(0.0454)
Patrolling	0.821***	0.881***	0.925***	0.878**
	(0.0228)	(0.0349)	(0.0250)	(0.0500)
vs DTO	0.957	0.887***	1.005	0.964
	(0.0306)	(0.0402)	(0.0329)	(0.0633)
Operations	1.002	1.035	1.108***	1.166**
	(0.0272)	(0.0427)	(0.0309)	(0.0757)
Police violence	1.063**	1.164***	1.034	1.615***
	(0.0302)	(0.0590)	(0.0339)	(0.0891)
Neighborhood police	1.022	1.050	1.047*	1.109**
	(0.0272)	(0.0359)	(0.0271)	(0.0515)
Constant	0.00892***	0.00168***	0.00314***	0.0168***
	(0.00151)	(0.000388)	(0.000580)	(0.00421)
Year*State FE	Yes	Yes	Yes	Yes
Observations	445,147	418,254	445,126	445,164

Clustered standard errors by municipality.
Observations weighted by household weights.
*** p<0.01, ** p<0.05, * p<0.1

A3. Self-help Activities

VARIABLES	Lock	Alarm	Private security	Neighborhood organization	Insurance	Dog	Migration	Guns
Individual demographics	**(odds ratio)**	**(odds ratio)**	**(odds ratio)**	**(odds ratio)**	**(odds ratio)**	**(odds ratio)**	**(odds ratio)**	**(odds ratio)**
Male	0.924***	1.023	0.932*	1.003	1.189***	1.126***	0.819***	1.643***
	(0.0132)	(0.0287)	(0.0355)	(0.0172)	(0.0433)	(0.0281)	(0.0340)	(0.114)
Age	1.023***	1.058***	1.032***	1.047***	1.038***	1.027***	1.029***	1.048***
	(0.00253)	(0.00756)	(0.00794)	(0.00358)	(0.00786)	(0.00506)	(0.00909)	(0.0126)
Age2	1.000***	0.999***	1.000***	1.000***	1.000***	1.000***	0.999***	0.999***
	(2.68e-05)	(8.46e-05)	(8.68e-05)	(3.86e-05)	(9.37e-05)	(6.07e-05)	(0.000111)	(0.00013)
Family size	0.983***	0.996	0.965**	1.006	0.971**	1.031***	0.910***	1.001
	(0.00397)	(0.0121)	(0.0134)	(0.00486)	(0.0122)	(0.00986)	(0.0138)	(0.0245)
Employed	1.070***	0.944	0.915**	1.015	1.161***	1.026	1.039	1.267***
	(0.0157)	(0.0356)	(0.0383)	(0.0186)	(0.0486)	(0.0301)	(0.0524)	(0.0967)
Years of schooling and local context								
Lower secondary education	1.378***	1.525**	1.915***	1.148***	1.811***	1.329***	0.985	1.414**
	(0.0517)	(0.272)	(0.386)	(0.0556)	(0.369)	(0.0861)	(0.184)	(0.223)
Upper secondary education	1.779***	4.020***	3.150***	1.476***	2.713***	1.907***	1.276	1.500**
	(0.0835)	(0.811)	(0.776)	(0.106)	(0.544)	(0.159)	(0.321)	(0.281)
Higher education	2.032***	9.346***	6.879***	1.420***	5.400***	2.070***	1.700**	2.596***
	(0.128)	(1.773)	(1.438)	(0.107)	(1.000)	(0.180)	(0.385)	(0.541)
Lower secondary education*Urban	0.932*	1.160	0.756	1.017	0.830	0.900	1.021	0.908
	(0.0388)	(0.230)	(0.168)	(0.0608)	(0.184)	(0.0736)	(0.210)	(0.174)
Upper secondary education*Urban	0.835***	0.814	0.674	0.944	0.972	0.705***	0.768	0.986
	(0.0427)	(0.173)	(0.179)	(0.0753)	(0.206)	(0.0697)	(0.201)	(0.205)
Higher education*Urban	0.838***	0.566***	0.412***	1.207**	0.921	0.641***	0.606**	0.728
	(0.0552)	(0.115)	(0.0928)	(0.100)	(0.184)	(0.0652)	(0.139)	(0.168)
Urban	1.436***	2.405***	2.693***	0.888**	1.666***	1.313***	1.721***	0.882
	(0.0527)	(0.381)	(0.477)	(0.0467)	(0.264)	(0.0846)	(0.251)	(0.133)
Local characteristics								
Deprivation index 2010	0.827***	0.552***	0.432***	0.876***	0.613***	0.987	0.782***	1.189***
	(0.0188)	(0.0325)	(0.0390)	(0.0331)	(0.0378)	(0.0277)	(0.0521)	(0.0587)

Usos y Costumbres	0.962	0.775	1.4286	0.828	1.054	0.676**	0.801	0.760
	(0.0837)	(0.199)	(0.740)	(0.132)	(0.301)	(0.108)	(0.336)	(0.196)
Individual victimization								
Victim (before)	1.219***	1.057	1.188***	1.154***	1.290***	1.142***	1.271***	1.147
	(0.0278)	(0.0416)	(0.0656)	(0.0320)	(0.0639)	(0.0419)	(0.0882)	(0.102)
Theft	2.028***	1.760***	1.302***	1.437***	1.640***	1.656***	1.759***	2.000***
	(0.0333)	(0.0616)	(0.0466)	(0.0228)	(0.0514)	(0.0384)	(0.0771)	(0.0844)
Fraud	1.285***	1.390***	1.292***	1.260***	1.390***	1.172***	1.294***	1.237***
	(0.0289)	(0.0532)	(0.0523)	(0.0347)	(0.0504)	(0.0434)	(0.0729)	(0.0878)
Threats and bodily harm	1.131***	1.005	0.971	1.054***	1.028	1.139***	1.330***	1.216***
	(0.0153)	(0.0287)	(0.0526)	(0.0214)	(0.0308)	(0.0222)	(0.0391)	(0.0705)
Extortion	1.448***	1.512***	1.272***	1.284***	1.507***	1.232***	1.161**	1.340***
	(0.0363)	(0.0739)	(0.0882)	(0.0381)	(0.0843)	(0.0547)	(0.0846)	(0.132)
Kidnapping	1.427**	2.159***	2.315***	1.207	2.288***	1.249	3.576***	2.741***
	(0.228)	(0.411)	(0.706)	(0.254)	(0.699)	(0.252)	(1.015)	(0.915)
Sexual crimes	1.041*	0.881**	0.984	1.026	1.067	0.931*	1.054	1.021
	(0.0253)	(0.0468)	(0.0535)	(0.0239)	(0.0592)	(0.0347)	(0.0425)	(0.0635)
Neighborhood characteristics								
Substances	1.044***	0.765***	0.822***	0.895***	0.876***	1.045**	0.935**	1.063
	(0.0118)	(0.0228)	(0.0357)	(0.0154)	(0.0292)	(0.0207)	(0.0298)	(0.0592)
Non-violent crimes	1.163***	1.172***	1.182***	1.208***	1.156***	1.072***	1.135***	1.046
	(0.0171)	(0.0384)	(0.0410)	(0.0202)	(0.0479)	(0.0246)	(0.0449)	(0.0575)
Violent crimes	1.089***	1.236***	1.103**	1.073***	1.147***	1.093***	1.140***	1.324***
	(0.0139)	(0.0384)	(0.0431)	(0.0185)	(0.0417)	(0.0251)	(0.0477)	(0.0727)
Fights	1.087***	0.889***	0.983	0.956*	0.992	1.057*	1.052	1.031
	(0.0230)	(0.0401)	(0.0591)	(0.0234)	(0.0572)	(0.0336)	(0.0610)	(0.0866)
Gunshots	1.205***	1.113**	1.048	1.137***	1.019	1.235***	1.154**	1.224**
	(0.0224)	(0.0537)	(0.0534)	(0.0342)	(0.0500)	(0.0481)	(0.0732)	(0.106)
Gangs	1.305***	0.987	1.014	1.106***	0.927	1.240***	1.233***	0.963
	(0.0213)	(0.0402)	(0.0470)	(0.0279)	(0.0489)	(0.0328)	(0.0701)	(0.0663)
Extortion	1.268***	1.281***	1.103	1.143***	1.340***	1.206***	1.088	1.256***
	(0.0242)	(0.0533)	(0.0699)	(0.0359)	(0.0751)	(0.0419)	(0.0669)	(0.106)
Institutional development								
Public goods	1.069***	0.885***	0.885***	1.042**	0.975	1.043**	0.987	0.955

	(0.0138)	(0.0250)	(0.0306)	(0.0178)	(0.0399)	(0.0204)	(0.0396)	(0.0654)
Economic programs	0.994	0.867***	0.885***	1.030	0.960	0.996	1.000	0.992
	(0.0110)	(0.0253)	(0.0358)	(0.0201)	(0.0304)	(0.0194)	(0.0340)	(0.0566)
Engagement Programs	1.172***	1.116***	1.004	1.373***	1.149***	1.132***	1.051	1.019
	(0.0137)	(0.0306)	(0.0368)	(0.0223)	(0.0373)	(0.0266)	(0.0416)	(0.0568)
Patrolling	0.898***	0.860***	0.819***	0.953	0.909**	0.895***	0.918	0.887
	(0.0151)	(0.0277)	(0.0448)	(0.0284)	(0.0400)	(0.0246)	(0.0523)	(0.0682)
vs DTO	0.936***	0.912**	0.996	0.900***	1.070	1.004	1.136**	1.136
	(0.0158)	(0.0392)	(0.0545)	(0.0274)	(0.0480)	(0.0324)	(0.0685)	(0.111)
Operations	1.167***	1.068*	0.993	1.207***	1.147***	1.120***	1.173**	1.150**
	(0.0198)	(0.0390)	(0.0607)	(0.0322)	(0.0533)	(0.0296)	(0.0725)	(0.0779)
Police violence	1.054***	1.051	0.978	1.099***	1.024	1.074*	1.015	1.282***
	(0.0202)	(0.0565)	(0.0580)	(0.0294)	(0.0525)	(0.0392)	(0.0585)	(0.107)
Neighborhood police	1.201***	1.608***	4.312***	1.985***	1.602***	1.242***	1.274***	1.311***
	(0.0161)	(0.0432)	(0.149)	(0.0366)	(0.0555)	(0.0274)	(0.0513)	(0.0659)
Constant	0.0794***	0.000707***	0.000808***	0.0360***	0.00115***	0.0240***	0.0180***	0.00279***
	(0.00639)	(0.000193)	(0.000263)	(0.00429)	(0.000280)	(0.00379)	(0.00561)	(0.00114)
Year*State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	416,273	416,122	415,858	415,583	415,985	416,378	416,134	416,253

Clustered standard errors by municipality.

Observation weighted by household weights.

*** p<0.01, ** p<0.05, * p<0.1

A4. Perception of Municipal Police Corruption and Ineffectiveness

VARIABLES	Corruption	Ineffectiveness
Individual demographics	**(odds ratio)**	**(odds ratio)**
Male	1.003	1.034**
	(0.0159)	(0.0162)
Age	1.013***	1.027***
	(0.00278)	(0.00215)
Age2	1.000***	1.000***
	(2.98e-05)	(2.35e-05)
Family size	0.989**	1.001
	(0.00447)	(0.00346)
Employed	1.067***	1.038**
	(0.0168)	(0.0157)
Years of schooling and local context		
Lower secondary education	1.029	1.008
	(0.0335)	(0.0295)
Upper secondary education	1.171***	0.956
	(0.0561)	(0.0420)
Higher education	1.172**	1.070
	(0.0746)	(0.0555)
Lower secondary education*Urban	1.010	0.933**
	(0.0409)	(0.0306)
Upper secondary education*Urban	0.905*	0.939
	(0.0482)	(0.0441)
Higher education*Urban	1.019	0.869**
	(0.0677)	(0.0485)
Urban	1.253***	1.290***
	(0.0400)	(0.0360)
Local characteristics		
Deprivation index 2010	0.774***	0.908***
	(0.0221)	(0.0194)
Usos y Costumbres	0.502***	0.578***
	(0.0520)	(0.0500)
Individual victimization		
Victim (before)	1.183***	1.067***
	(0.0311)	(0.0227)
Theft	1.213***	1.142***
	(0.0231)	(0.0217)
Fraud	1.126***	1.108***
	(0.0357)	(0.0279)
Threats and bodily harm	1.063***	1.052***
	(0.0212)	(0.0177)
Extortion	1.154***	1.110***
	(0.0360)	(0.0323)
Kidnapping	1.679**	1.142
	(0.416)	(0.249)

Sexual crimes	1.044	1.019
	(0.0363)	(0.0242)
Neighborhood characteristics		
Substances	1.315***	1.177***
	(0.0163)	(0.0134)
Non-violent crimes	1.121***	1.074***
	(0.0183)	(0.0144)
Violent crimes	1.059***	1.084***
	(0.0181)	(0.0128)
Fights	1.025	1.049***
	(0.0197)	(0.0189)
Gunshots	1.172***	1.163***
	(0.0307)	(0.0281)
Gangs	1.098***	1.039**
	(0.0223)	(0.0162)
Extortion	1.138***	1.092***
	(0.0338)	(0.0267)
Institutional development		
Public goods	0.887***	0.847***
	(0.0136)	(0.0137)
Economic programs	0.829***	0.828***
	(0.0134)	(0.0106)
Engagement Programs	0.879***	0.847***
	(0.0124)	(0.0113)
Patrolling	0.711***	0.661***
	(0.0148)	(0.0118)
vs DTO	0.915***	0.889***
	(0.0207)	(0.0178)
Operations	1.052***	0.962**
	(0.0201)	(0.0158)
Police violence	1.613***	1.492***
	(0.0403)	(0.0310)
Neighborhood police	0.985	0.948***
	(0.0149)	(0.0160)
Constant	2.085***	0.873
	(0.273)	(0.101)
Year*State FE	Yes	Yes
Observations	271,038	287,421

Clustered standard errors by municipality.
Observation weighted by household weights.
*** p<0.01, ** p<0.05, * p<0.1

A5. Distrust of Police

VARIABLES	Municipal	Transit	State	Federal	Army	Navy	Judicial	Judges	MP
Individual demographics									
Male	1.032**	1.052***	0.973*	0.817***	0.732***	0.744***	1.048**	0.992	1.009
	(0.0156)	(0.0172)	(0.0156)	(0.0124)	(0.0157)	(0.0186)	(0.0218)	(0.0217)	(0.0176)
Age	1.026***	1.016***	1.033***	1.026***	1.008***	1.007**	1.049***	1.018***	1.046***
	(0.00218)	(0.00211)	(0.00257)	(0.00269)	(0.00212)	(0.00301)	(0.00331)	(0.00431)	(0.00321)
Age2	1.000***	1.000***	1.000***	1.000***	1.000***	1.000**	1.000***	1.000***	1.000***
	(2.29e-05)	(2.27e-05)	(2.73e-05)	(2.86e-05)	(2.26e-05)	(3.40e-05)	(3.49e-05)	(4.86e-05)	(3.46e-05)
Family size	1.005	0.996	0.998	1.001	0.999	0.999	0.993	0.993	0.987**
	(0.00347)	(0.00445)	(0.00342)	(0.00389)	(0.00451)	(0.00607)	(0.00509)	(0.00786)	(0.00564)
Employed	0.997	0.994	1.021	1.007	0.988	0.990	1.044**	0.996	1.026
	(0.0143)	(0.0156)	(0.0150)	(0.0126)	(0.0158)	(0.0202)	(0.0196)	(0.0253)	(0.0202)
Years of schooling and local context									
Lower secondary education	1.055*	0.878***	0.921**	0.928**	0.865***	0.808***	0.977	0.901*	0.953
	(0.0318)	(0.0322)	(0.0314)	(0.0311)	(0.0295)	(0.0419)	(0.0378)	(0.0497)	(0.0419)
Upper secondary education	0.988	0.907**	0.831***	0.828***	0.690***	0.690***	0.942	0.896	0.945
	(0.0406)	(0.0425)	(0.0363)	(0.0353)	(0.0336)	(0.0469)	(0.0521)	(0.0665)	(0.0545)
Higher education	0.973	0.924	0.925	0.847***	0.806***	0.714***	1.048	0.959	1.079
	(0.0518)	(0.0538)	(0.0514)	(0.0473)	(0.0457)	(0.0616)	(0.0698)	(0.0707)	(0.0722)
Lower secondary education*Urban	0.894***	1.073	1.022	1.001	1.029	1.073	1.006	1.020	0.995
	(0.0319)	(0.0467)	(0.0388)	(0.0411)	(0.0408)	(0.0621)	(0.0476)	(0.0679)	(0.0561)
Upper secondary education*Urban	0.852***	0.954	1.076	1.069	1.285***	1.184**	1.068	0.995	0.999
	(0.0405)	(0.0511)	(0.0526)	(0.0515)	(0.0688)	(0.0848)	(0.0666)	(0.0810)	(0.0673)
Higher education*Urban	0.882**	0.950	1.052	1.082	1.210***	1.178*	1.071	0.910	0.950
	(0.0504)	(0.0591)	(0.0621)	(0.0632)	(0.0765)	(0.108)	(0.0772)	(0.0721)	(0.0686)
Urban	1.261***	1.066*	1.071**	1.093***	1.013	0.993	1.149***	1.198***	1.176***
	(0.0350)	(0.0395)	(0.0334)	(0.0350)	(0.0328)	(0.0398)	(0.0431)	(0.0588)	(0.0518)
Local characteristics									
Deprivation index 2010	0.920***	0.867***	0.894***	1.010	1.017	1.000	0.938***	0.948**	0.948***
	(0.0184)	(0.0206)	(0.0177)	(0.0194)	(0.0220)	(0.0266)	(0.0188)	(0.0228)	(0.0183)
Usos y Costumbres	0.584***	0.778*	1.18	1.128	1.065	0.96	0.899	0.903	0.864
	(0.0501)	(0.102)	(0.108)	(0.0989)	(0.0900)	(0.118)	(0.0893)	(0.120)	(0.100)

Individual victimization									
Victim (before)	1.046**	1.074***	1.053***	1.032	0.993	0.933**	1.111***	1.095***	1.109***
	(0.0221)	(0.0231)	(0.0194)	(0.0227)	(0.0251)	(0.0284)	(0.0254)	(0.0310)	(0.0277)
Theft	1.175***	1.144***	1.130***	1.038***	1.050**	0.966	1.096***	1.024	1.104***
	(0.0187)	(0.0197)	(0.0165)	(0.0128)	(0.0201)	(0.0207)	(0.0223)	(0.0264)	(0.0228)
Fraud	1.098***	1.051**	1.115***	1.060***	1.066**	1.030	1.105***	1.061*	1.128***
	(0.0263)	(0.0230)	(0.0236)	(0.0229)	(0.0278)	(0.0311)	(0.0307)	(0.0370)	(0.0336)
Threats and bodily harm	1.069***	1.040*	1.027*	1.003	1.026	1.041*	0.999	1.009	1.030
	(0.0164)	(0.0210)	(0.0164)	(0.0151)	(0.0195)	(0.0233)	(0.0207)	(0.0273)	(0.0211)
Extortion	1.139***	1.082***	1.084***	1.070**	1.035	1.018	1.111***	1.053	1.091**
	(0.0334)	(0.0284)	(0.0287)	(0.0314)	(0.0288)	(0.0376)	(0.0379)	(0.0433)	(0.0385)
Kidnapping	1.184	0.959	1.062	1.307	0.886	0.663*	1.168	1.341	1.412
	(0.256)	(0.232)	(0.197)	(0.220)	(0.182)	(0.158)	(0.250)	(0.445)	(0.308)
Sexual crimes	1.020	0.951*	1.038	1.009	1.067***	1.020	0.972	1.007	0.958
	(0.0252)	(0.0262)	(0.0245)	(0.0273)	(0.0243)	(0.0295)	(0.0326)	(0.0464)	(0.0315)
Neighborhood characteristics									
Substances	1.124***	1.121***	1.066***	1.040***	0.992	1.009	1.083***	1.069***	1.089***
	(0.0133)	(0.0137)	(0.0113)	(0.0112)	(0.0135)	(0.0198)	(0.0144)	(0.0191)	(0.0154)
Non-violent crimes	1.053***	1.062***	1.067***	1.083***	1.039***	1.041**	1.102***	1.092***	1.091***
	(0.0130)	(0.0128)	(0.0133)	(0.0142)	(0.0152)	(0.0182)	(0.0188)	(0.0201)	(0.0173)
Violent crimes	1.061***	1.047***	1.043***	1.037***	1.051***	1.043**	1.056***	1.069***	1.060***
	(0.0144)	(0.0154)	(0.0146)	(0.0141)	(0.0138)	(0.0183)	(0.0166)	(0.0199)	(0.0178)
Fights	1.056***	1.081***	1.038**	1.075***	1.142***	1.137***	1.028	1.066**	1.027
	(0.0182)	(0.0179)	(0.0169)	(0.0186)	(0.0234)	(0.0273)	(0.0208)	(0.0313)	(0.0232)
Gunshots	1.154***	1.117***	1.109***	1.085***	1.069***	1.065**	1.054**	1.119***	1.056*
	(0.0250)	(0.0246)	(0.0267)	(0.0229)	(0.0229)	(0.0309)	(0.0259)	(0.0336)	(0.0315)
Gangs	1.033**	0.987	1.039**	0.983	1.031	1.035	0.940***	0.979	0.927***
	(0.0158)	(0.0149)	(0.0161)	(0.0160)	(0.0199)	(0.0282)	(0.0202)	(0.0267)	(0.0229)
Extortion	1.134***	1.094***	1.130***	1.042*	1.059**	1.020	1.122***	0.996	1.076***
	(0.0248)	(0.0236)	(0.0230)	(0.0247)	(0.0267)	(0.0282)	(0.0251)	(0.0377)	(0.0291)
Institutional development									
Public goods	0.872***	0.864***	0.863***	0.853***	0.855***	0.829***	0.879***	0.828***	0.881***
	(0.0130)	(0.0151)	(0.0122)	(0.0123)	(0.0148)	(0.0193)	(0.0143)	(0.0207)	(0.0155)
Economic programs	0.841***	0.851***	0.857***	0.880***	0.911***	0.916***	0.827***	0.842***	0.838***

	(0.0105)	(0.0116)	(0.0106)	(0.0102)	(0.0123)	(0.0160)	(0.0101)	(0.0144)	(0.0118)
Engagement Programs	0.860***	0.864***	0.893***	0.910***	0.918***	0.948***	0.881***	0.894***	0.864***
	(0.0125)	(0.0114)	(0.0124)	(0.0114)	(0.0125)	(0.0176)	(0.0118)	(0.0176)	(0.0148)
Patrolling	0.685***	0.784***	0.749***	0.797***	0.818***	0.794***	0.797***	0.835***	0.812***
	(0.0114)	(0.0122)	(0.0107)	(0.0141)	(0.0135)	(0.0162)	(0.0155)	(0.0183)	(0.0181)
vs DTO	0.883***	0.891***	0.855***	0.853***	0.850***	0.805***	0.846***	0.861***	0.879***
	(0.0177)	(0.0193)	(0.0162)	(0.0177)	(0.0189)	(0.0257)	(0.0173)	(0.0248)	(0.0207)
Operations	1.006	0.989	0.949***	0.898***	0.861***	0.850***	0.989	0.949**	0.962**
	(0.0163)	(0.0172)	(0.0138)	(0.0145)	(0.0173)	(0.0213)	(0.0183)	(0.0224)	(0.0185)
Police violence	1.461***	1.355***	1.301***	1.188***	1.212***	1.149***	1.193***	1.187***	1.212***
	(0.0343)	(0.0357)	(0.0279)	(0.0226)	(0.0271)	(0.0297)	(0.0286)	(0.0333)	(0.0318)
Neighborhood police	0.984	0.985	0.983	1.006	1.036**	1.023	1.010	0.999	0.980
	(0.0151)	(0.0135)	(0.0149)	(0.0149)	(0.0166)	(0.0213)	(0.0132)	(0.0173)	(0.0172)
Constant	1.121	1.356***	0.465***	0.517***	0.232***	0.194***	0.728	0.877	0.606***
	(0.0868)	(0.129)	(0.0738)	(0.0549)	(0.0409)	(0.0246)	(0.188)	(0.139)	(0.0542)
Year*State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	289,314	270,843	277,564	271,460	364,672	262,089	173,144	98,613	165,703

Clustered standard errors by municipality.

Observation weighted by household weights.

*** p<0.01, ** p<0.05, * p<0.1

A6. Interpersonal Distrust

VARIABLES	Family	Neighbors
Individual demographics		
Male	0.911***	0.812***
	(0.0227)	(0.0116)
Age	1.036***	0.982***
	(0.00336)	(0.00206)
Age2	1.000***	1.000
	(3.37e-05)	(2.24e-05)
Family size	0.986***	1.001
	(0.00503)	(0.00439)
Employed	0.890***	1.019
	(0.0223)	(0.0152)
Years of schooling and local context		
Lower secondary education	0.811***	0.912***
	(0.0332)	(0.0259)
Upper secondary education	0.580***	0.780***
	(0.0351)	(0.0319)
Higher education	0.478***	0.636***
	(0.0499)	(0.0340)
Lower secondary education*Urban	0.867***	0.951
	(0.0415)	(0.0315)
Upper secondary education*Urban	0.789***	0.935
	(0.0544)	(0.0425)
Higher education*Urban	0.626***	0.937
	(0.0697)	(0.0535)
Urban	1.069*	1.264***
	(0.0374)	(0.0326)
Local characteristics		
Deprivation index 2010	1.168***	1.011
	(0.0207)	(0.0187)
Usos y Costumbres	0.969	1.112
	(0.0901)	(0.0875)
Individual victimization		
Victim (before)	0.981	1.004
	(0.0318)	(0.0210)
Theft	1.076***	1.132***
	(0.0250)	(0.0216)
Fraud	0.923*	0.904***
	(0.0385)	(0.0205)
Threats and bodily harm	1.129***	1.162***
	(0.0262)	(0.0174)
Extortion	0.963	0.945**
	(0.0399)	(0.0260)
Kidnapping	1.443*	1.480**
	(0.308)	(0.247)
Sexual crimes	1.092***	1.043*

	(0.0325)	(0.0227)
Neighborhood characteristics		
Substances	1.077***	1.115***
	(0.0177)	(0.0114)
Non-violent crimes	1.056***	1.085***
	(0.0208)	(0.0149)
Violent crimes	1.059***	1.029**
	(0.0221)	(0.0132)
Fights	1.458***	1.704***
	(0.0335)	(0.0333)
Gunshots	1.138***	1.097***
	(0.0351)	(0.0257)
Gangs	1.174***	1.319***
	(0.0308)	(0.0224)
Extortion	1.071**	0.949**
	(0.0342)	(0.0215)
Institutional development		
Public goods	0.914***	0.895***
	(0.0184)	(0.0107)
Economic programs	1.003	0.971**
	(0.0169)	(0.0110)
Engagement Programs	1.015	0.947***
	(0.0210)	(0.0111)
Patrolling	0.853***	0.868***
	(0.0185)	(0.0134)
vs DTO	0.957	0.963**
	(0.0290)	(0.0175)
Operations	0.916***	0.971*
	(0.0203)	(0.0153)
Police violence	1.142***	1.031
	(0.0363)	(0.0224)
Neighborhood police	1.015	0.927***
	(0.0244)	(0.0135)
Constant	0.0878***	0.747***
	(0.0110)	(0.0523)
Year*State FE	Yes	Yes
Observations	321,463	320,792

Clustered standard errors by municipality.
Observations weighted by household weights.
*** p<0.01, ** p<0.05, * p<0.1

A7. Control de Confianza

VARIABLES	Municipal	State
Control de Confianza		
Progress	-0.001	-0.001
	(0.018)	(0.015)
Individual demographics		
Male	0.006**	-0.008**
	(0.003)	(0.004)
Age	0.004***	0.008***
	(0.001)	(0.001)
Age2	-0.000***	-0.000***
	(0.000)	(0.000)
Family size	-0.001	-0.002**
	(0.001)	(0.001)
Employed	0.008**	0.009***
	(0.003)	(0.003)
Education	0.008***	0.020***
	(0.001)	(0.002)
Local characteristics		
Urban	0.067***	0.040***
	(0.005)	(0.006)
Deprivation index 2010	-0.030***	-0.041***
	(0.005)	(0.005)
Usos y Costumbres	-0.159***	0.042**
	(0.022)	(0.019)
Individual victimization		
Victim (before)	0.031***	0.025***
	(0.004)	(0.004)
Theft	0.049***	0.044***
	(0.003)	(0.004)
Fraud	0.043***	0.053***
	(0.010)	(0.012)
Wounds	0.059***	0.017
	(0.015)	(0.017)
Extortion	0.038***	0.032***
	(0.006)	(0.007)
Kidnapping	0.117**	0.054
	(0.045)	(0.044)
Sexual crimes	0.027*	0.006
	(0.016)	(0.018)
Neighborhood characteristics		
Substances	0.036***	0.021***
	(0.003)	(0.002)
Low-impact crimes	0.027***	0.026***
	(0.004)	(0.004)

High-impact crimes	0.035***	0.027***
	(0.005)	(0.005)
Shots	0.051***	0.035***
	(0.004)	(0.005)
Gangs	0.018***	0.010***
	(0.003)	(0.004)
Extortion	0.042***	0.042***
	(0.005)	(0.006)
Institutional development		
Public goods	-0.046***	-0.051***
	(0.004)	(0.003)
Economic programs	-0.052***	-0.056***
	(0.003)	(0.003)
Engagement Programs	-0.047***	-0.040***
	(0.002)	(0.003)
Patrolling	-0.103***	-0.085***
	(0.004)	(0.003)
vs DTO	-0.035***	-0.048***
	(0.005)	(0.004)
Neighborhood police	-0.015***	-0.005
	(0.003)	(0.003)
Constant	1.937***	1.663***
	(0.024)	(0.031)
Year FE	Yes	Yes
State FE	Yes	Yes
Observations	294,692	278,599
R-squared	0.091	0.093

Clustered standard errors by municipality.
Observations weighted by household weights.
*** p<0.01, ** p<0.05, * p<0.1

A8. Officers per Capita

VARIABLES	Municipal	State
Police force per capita		
Officers per capita	1.050	1.036
	(0.0506)	(0.0429)
Individual demographics		
Male	1.026*	0.968**
	(0.0154)	(0.0155)
Age	1.026***	1.034***
	(0.00221)	(0.00256)
Age2	1.000***	1.000***
	(2.34e-05)	(2.73e-05)
Family size	1.005	0.997
	(0.00346)	(0.00337)
Employed	1.000	1.020
	(0.0144)	(0.0151)
Education	0.954***	0.989
	(0.00643)	(0.00785)
Local characteristics		
Urban	1.175***	1.094***
	(0.0251)	(0.0251)
Deprivation index 2010	0.920***	0.895***
	(0.0185)	(0.0183)
Usos y Costumbres	0.609***	1.218**
	(0.0525)	(0.116)
Individual victimization		
Victim (before)	1.037	1.047**
	(0.0231)	(0.0191)
Theft	1.171***	1.129***
	(0.0187)	(0.0169)
Fraud	1.097***	1.121***
	(0.0266)	(0.0245)
Wounds	1.068***	1.027*
	(0.0164)	(0.0166)
Extortion	1.143***	1.090***
	(0.0339)	(0.0296)
Kidnapping	1.186	1.046
	(0.260)	(0.197)
Sexual crimes	1.016	1.038
	(0.0250)	(0.0251)
Neighborhood characteristics		
Substances	1.121***	1.061***
	(0.0134)	(0.0114)
Low-impact crimes	1.053***	1.067***
	(0.0132)	(0.0134)

High-impact crimes	1.059***	1.043***
	(0.0147)	(0.0151)
Fights	1.054***	1.039**
	(0.0184)	(0.0172)
Shots	1.157***	1.110***
	(0.0270)	(0.0281)
Gangs	1.033**	1.040**
	(0.0163)	(0.0164)
Extortion	1.127***	1.127***
	(0.0245)	(0.0235)
Institutional development		
Public goods	0.874***	0.863***
	(0.0134)	(0.0127)
Economic programs	0.840***	0.856***
	(0.0102)	(0.0106)
Engagement Programs	0.862***	0.894***
	(0.0129)	(0.0128)
Patrolling	0.682***	0.749***
	(0.0117)	(0.0110)
vs DTO	0.882***	0.855***
	(0.0180)	(0.0164)
Police operations	1.006	0.948***
	(0.0170)	(0.0139)
Police violence	1.456***	1.305***
	(0.0341)	(0.0280)
Neighborhood police	0.985	0.987
	(0.0151)	(0.0147)
Constant	0.820***	0.353***
	(0.0588)	(0.0291)
Year FE	Yes	Yes
State FE	Yes	Yes
Observations	289,314	274,551

Clustered standard errors by municipality.
Observations weighted by household weights.
*** p<0.01, ** p<0.05, * p<0.1

A9. Joint Operations

VARIABLES	Municipal	State	Federal	Army	Navy
Joint operations					
Joint operations	1.194	1.555***	1.012	1.053	1.060
	(0.135)	(0.0930)	(0.0725)	(0.0656)	(0.0762)
Individual demographics					
Male	0.984	0.900***	0.774***	0.670***	0.652***
	(0.0358)	(0.0304)	(0.0235)	(0.0233)	(0.0324)
Age	1.036***	1.043***	1.033***	1.007	1.011*
	(0.00551)	(0.00529)	(0.00542)	(0.00481)	(0.00695)
Age2	1.000***	1.000***	1.000***	1.000	1.000
	(5.59e-05)	(5.58e-05)	(5.67e-05)	(4.99e-05)	(7.60e-05)
Family size	1.007	0.995	0.977***	0.998	0.984
	(0.00783)	(0.00820)	(0.00814)	(0.00877)	(0.0133)
Employed	1.000	1.066**	1.002	0.937*	0.944
	(0.0343)	(0.0309)	(0.0304)	(0.0365)	(0.0455)
Education	0.979	1.019	0.989	1.025	0.942**
	(0.0172)	(0.0154)	(0.0148)	(0.0198)	(0.0224)
Local characteristics					
Urban	1.198***	1.152***	1.206***	1.145***	1.082
	(0.0526)	(0.0519)	(0.0545)	(0.0529)	(0.0618)
Deprivation index 2010	1.114***	1.013	1.161***	1.173***	1.188***
	(0.0395)	(0.0376)	(0.0439)	(0.0454)	(0.0546)
Usos y Costumbres	0.680***	1.224*	1.320**	1.3191***	1.1523
	(0.0845)	(0.147)	(0.171)	(0.143)	(0.1959)
Individual victimization					
Victim (before)	0.948	1.105**	1.053	0.978	0.856**
	(0.0727)	(0.0477)	(0.0648)	(0.0580)	(0.0582)
Theft	1.143***	1.141***	1.037	1.026	0.963
	(0.0516)	(0.0425)	(0.0336)	(0.0385)	(0.0454)
Fraud	1.112	1.056	1.118**	1.122**	1.121
	(0.0770)	(0.0534)	(0.0609)	(0.0626)	(0.0896)
Threats and wounds	1.087**	1.010	1.009	0.991	1.058
	(0.0449)	(0.0389)	(0.0289)	(0.0323)	(0.0452)
Extortion	1.207***	1.099	1.041	1.060	0.953
	(0.0742)	(0.0730)	(0.0613)	(0.0666)	(0.0722)
Kidnapping	3.453***	2.515***	1.837*	1.683	3.113***
	(1.629)	(0.796)	(0.622)	(0.601)	(1.057)
Sexual crimes	1.000	1.105	0.955	1.115**	1.106
	(0.0558)	(0.0698)	(0.0678)	(0.0481)	(0.0814)
Neighborhood characteristics					
Substances	1.100***	1.054*	0.995	0.950*	0.969
	(0.0301)	(0.0297)	(0.0252)	(0.0272)	(0.0318)
Low-impact crimes	1.073**	1.099***	1.114***	1.142***	1.144***
	(0.0313)	(0.0338)	(0.0327)	(0.0354)	(0.0465)

High-impact crimes	1.024	1.016	1.059*	1.039	1.072*
	(0.0355)	(0.0310)	(0.0339)	(0.0331)	(0.0399)
Fights	0.978	1.044	1.089*	1.108**	1.155**
	(0.0361)	(0.0380)	(0.0482)	(0.0464)	(0.0701)
Shots	1.167***	1.119**	1.050	1.066	1.069
	(0.0481)	(0.0533)	(0.0445)	(0.0437)	(0.0569)
Gangs	1.115***	1.088**	1.036	1.083**	1.083*
	(0.0394)	(0.0435)	(0.0408)	(0.0405)	(0.0494)
Extortion	1.216***	1.223***	1.092*	1.036	1.019
	(0.0698)	(0.0558)	(0.0498)	(0.0544)	(0.0607)
Institutional development					
Public goods	0.863***	0.868***	0.826***	0.801***	0.794***
	(0.0341)	(0.0346)	(0.0282)	(0.0267)	(0.0345)
Economic programs	0.859***	0.851***	0.868***	0.880***	0.863***
	(0.0240)	(0.0231)	(0.0215)	(0.0252)	(0.0299)
Engagement Programs	0.851***	0.859***	0.893***	0.861***	0.928*
	(0.0333)	(0.0274)	(0.0294)	(0.0280)	(0.0391)
Patrolling	0.663***	0.754***	0.779***	0.821***	0.818***
	(0.0337)	(0.0235)	(0.0302)	(0.0317)	(0.0337)
vs DTO	0.900**	0.800***	0.840***	0.789***	0.750***
	(0.0427)	(0.0378)	(0.0338)	(0.0388)	(0.0499)
Police violence	1.503***	1.257***	1.121**	1.172***	1.113**
	(0.0803)	(0.0621)	(0.0505)	(0.0550)	(0.0577)
Neighborhood police	0.960	0.970	1.070*	1.015	0.999
	(0.0322)	(0.0320)	(0.0370)	(0.0306)	(0.0440)
Constant	1.034	0.457***	0.520***	0.274***	0.269***
	(0.141)	(0.0603)	(0.0717)	(0.0374)	(0.0461)
Observations	52,230	52,050	49,612	68,229	49,858

Clustered standard errors by municipality.
Observations weighted by household weights.
*** p<0.01, ** p<0.05, * p<0.1