Individual and community consequences and responses to organized violence: The case of the Mexican 'War on Organized Crime'

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Individual and community consequences and responses to organized violence:

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Abstract

Living in violent places can have numerous and profound consequences for people, including diminished mental, physical, and emotional wellbeing. However, the consequences of violent environments have overwhelmingly been examined in developed countries, particularly in the United States. This is an important limitation because the type and amount of violence that these developed countries experience is not representative of how violence manifests elsewhere in the world. In this dissertation I study the consequences of environmental violence before and during the Mexican 'War on Organized Crime' (WOC), a heavily militarized strategy that the Mexican government launched at the end of 2006 to control drug trafficking organizations (DTOs). Specifically, I leverage insights from environmental violence research in the United States and other developed countries and the distinctiveness of the Mexican context to examine how violence affects (1) children's cognitive performance, (2) weight gain, and (3) fear of crime.

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Introduction

Living in violent places can have numerous and profound consequences for people, including diminished mental, physical, and emotional wellbeing (Sharkey and Sampson, 2015; Sharkey, 2018). In these contexts, the presence of gangs, guns, and drugs is more likely, people are more likely to witness violence and find out about violent events in the community, and people might also become more anxious or fearful and adopt different strategies to avoid exposure to violence, shaping people's interactions and patterns of behavior and consumption. Violent places might also be characterized by disinvestment, infrastructural decline, limited employment opportunities, and population turnover (Yu and Lippert, 2016; Wilson, 1984). All of this can negatively affect people's lives, independently of whether an individual is directly exposed to violence or not.

However, the consequences of violent environments have overwhelmingly been examined in developed countries, particularly in the United States. Most violence in the United States is related to 'street crime' and is heavily concentrated in disadvantaged and racially segregated neighborhoods (Sampson, 2012; Sampson and Wilson, 1995). Yet, these environmental conditions are not necessarily representative of how crime and violence manifest elsewhere in the world. As a result, the consequences of environmental violence remain unclear in those contexts.

In contrast to the United States, in many developing countries violence is more widespread and extreme. By widespread I mean that middle-class and wealthy households and communities are exposed to crime and violence to a significant degree, which implies that crime and violence are not geographically constrained to disadvantaged neighborhoods, but rather extend to whole cities or even regions. In fact, middle-class and wealthy people are often specifically targeted in many crimes. Relatedly, I define extreme as particularly high average levels of violence, with many violent events being particularly brutal and psychologically impactful. Hence, violence is a phenomenon that many people experience in their daily lives in developing countries –regardless of their socioeconomic status or the community they live in– directly as victims or witnesses or indirectly through networks of friends and family and the media. The grisly nature of these violent events also magnifies the dissemination of information through these indirect means. The emotional, psychological, and behavioral adaptations that these events trigger can create ripple effects across large sections of society.

Latin America offers a great example of this type of widespread and extreme violence. Latin America is the deadliest region in the world, accounting for 8 percent of the population but a third of the homicides globally. Homicides in Brazil, Mexico, Colombia, and Venezuela represent a quarter of all the homicides in the world (Muggah and Aguirre Tabón, 2018). These extremely high levels of violence are the result of the political and organized nature of most violence in Latin America. Historically, violence in the region has been densely interwoven with organized crime and organized armed groups (e.g., militias, paramilitary groups), politics, and civic unrest. Even traditional 'street crime' is closely linked to politics and organized crime (Auyero, 2007; Villarreal and Yu, 2017). As such, much of this violence is only loosely tied to neighborhood deprivation and rather extends to whole cities or regions where political operatives and/or organized groups exert control or confront each other.

In this dissertation I study the consequences of environmental violence before and during the Mexican 'War on Organized Crime' (WOC), a heavily militarized strategy that the Mexican government launched at the end of 2006 to control drug trafficking organizations (DTOs). The effectiveness of the strategy has long been debated, but it has unmistakably caused a surge in violence. The national homicide rate tripled in a few years and although some regions remained relatively peaceful, many others experienced high levels of organized violence comparable to armed conflicts (Casey-Maslen, 2013). Violence during the WOC was not only extreme in terms of its frequency, but also in terms of its viciousness and brutality precisely because it resulted from confrontations between the army and DTOs and other organized armed groups across large regions of the country (Dell, 2015; Villarreal and Yu, 2017). Much of it was intended to produce fear and panic, for example, in the targeting of well-known politicians or journalists or in the public display of its gruesomeness (e.g., beheadings, dismemberments, signs of torture, corpses left in public places or hanging from bridges with *narco*-messages, street gun battles) (Shirk and Wallman, 2015).

Leveraging insights from environmental violence research in the United States and other developed countries and the distinctiveness of this novel context, I argue that the direction and size of the relationship between environmental violence and several important outcomes in Mexico differs from what prior research has uncovered in developed countries. This is because of the nature and intensity of violence, coupled with the specific socioeconomic, political, and public health conditions of this context, which enable responses and adaptations that are different in type and/or magnitude than in developed countries.

Specifically, I examine how environmental violence affects (1) children's cognitive performance, (2) weight gain, and (3) fear of crime. Prior research has shown a negative relationship between environmental violence and the first outcome and a positive association with the last two outcomes. My findings suggest that environmental violence has (1) an inverted U-shaped association with children's cognitive performance; (2) a positive association with weight gain that is stronger than that reported in previous research and that mostly affects females, young adults, and people with high socioeconomic status; and (3) a positive association with fear of crime that is moderated by collective efficacy.

Regarding children's cognitive performance I argue that the high levels and extreme nature of violence in much of Latin America has desensitized children and forced them to be vigilant as a behavioral adaptation to avoid victimization. I further argue that a short-term consequence of this adaptation is that new violent events require children to recruit fewer cognitive resources to inhibit the emotional response generated by such violence. This allows them to use more of these resources in whatever task is at hand –such as a cognitive test– and to focus on it. However, desensitization can lead to emotional numbing and despondency, whereas vigilance can become hypervigilance, a state of heightened anxiety that can lead to hyperactivity, chronic stress and exhaustion. This is especially the case when violence becomes too extreme and dramatic.

My findings in this study show an inverted U-shape impact of violence on the cognitive skills of children, consistent with these theoretical insights: as homicide rises cognitive scores also increase initially, but there is an inflection point in the level of homicides beyond which cognitive scores decrease substantially. Homicide levels beyond said inflection point are associated with the most extreme violence derived from the Mexican armed conflict. This study shows that the short-term consequences of environmental violence can be different in places that are accustomed to violence but that nonetheless have experienced extreme levels of it recently.

In my study on weight gain, I argue that we should expect an average positive impact of violence on weight gain that is *larger* than the impact found in developed countries. This is due to the widespread and extreme nature of much of the violence in Mexico, which can trigger stronger emotional (e.g., anxiety, fear) and behavioral (e.g., overeating, inactivity) responses and adaptations that are linked to excess weight than violence in developed countries. I also argue that the groups for which this association should be stronger are those that are already at high risk of being overweight or obese and/or that have been disproportionately involved in –or affected by– the extreme violence of the WOC. Specifically, I expect a *stronger* association between violence and (1) people with high socioeconomic status, (2) young adults, and (3) women. These groups are not necessarily those that are more fearful of violence or at risk of being overweight or obese in developed countries.

My findings in this study are consistent with both sets of hypotheses. I argue that violence is most strongly associated with weight gain among adults with high socioeconomic status (high education/occupational prestige) because this group has more access to food and the widespread and extreme nature of the violence in this context has created anxiety and fear even among middle-class and wealthy sectors of the population. Similarly, I argue that violence is most strongly associated with weight gain among young adults and women because they are more likely to suffer psychological distress as a consequence of said violence. This is the case even though young adults are on average less likely to be overweight or obese. This study shows that even though the direction of the association between violence and weight gain is the same as in the United States and other developed countries, extreme and widespread violence can have a more pronounced impact and disproportionately affect certain subgroups.

Lastly, in my study on fear of crime I re-conceptualize armed conflict and collective efficacy as signals that amplify or attenuate fear of crime. I define and operationalize armed conflict using its two essential characteristics according to international and humanitarian law: the presence of extreme violence and the Military and Organized Armed Groups (MOAG). Such armed conflicts, I argue, are foreign and extraordinary threats that signal a state of emergency beyond the community's control and as such should increase fear of crime. I further argue that, when facing the threat of armed conflict, collective efficacy signals that the community can be trusted and relied upon to provide moral support and some sense of control. In contrast, when armed conflict is absent, collective efficacy operates as a diffusion mechanism that spreads information about the few instances of violence present in the community, heightening awareness of these events. My findings are consistent with this theoretical framework. This study enhances our understanding of armed conflict and collective efficacy in a way that helps explain how they shape fear of crime. This theoretical framework specifies the conditions under which collective efficacy protects individuals from detrimental factors, as well as the conditions under which collective efficacy might enhance their negative consequences.

1

Environmental violence and children's cognitive performance in Mexico

Abstract

A growing literature indicates that violent environments impair children's cognitive performance, but this research has been carried out almost exclusively in large American cities. Crime and violence have distinct features in other places that might shape this relationship in different ways. In this chapter I develop a theoretical argument based on the concepts of violence normalization, desensitization, and vigilance to posit an inverted U-shape relationship between environmental violence and cognition in Latin America. I hypothesize that moderate increases in environmental violence make children more cautious and vigilant, which gives them a short-term concentration boost that allows them to perform better in cognitive tests. Yet there is an inflection point in the intensity of environmental violence beyond which the increased quantity and nature of the violence becomes overwhelming and unmanageable for children. This leads to emotional numbness and hypervigilance, hindering children's ability to focus on the test and lowering their performance. I assess this theoretical argument using data from before and during the Mexican 'War on Organized Crime', a heavily militarized organized crime control strategy. My findings are consistent with this conceptual framework, which implies a more complex relationship between environmental violence and cognitive performance than that uncovered by previous research.

Keywords: environmental violence, cognitive performance, desensitization, vigilance, Latin America

Introduction

Exposure to violence in childhood diminishes mental, physical, and emotional wellbeing, often throughout the life course (Margolin and Gordis, 2000; Delaney-Black et al., 2002; Foster and Brooks-Gunn, 2009). Despite these high stakes, only recently has a literature on 'environmental violence' begun to emerge indicating that violent *places* or *environments* can have deleterious consequences for children, too (Sharkey and Sampson, 2015; Sharkey, 2018). There is still little work on how environmental violence affects children's cognitive performance specifically, most of which has been carried out in large American cities (Los Angeles, Chicago) and has found a negative effect of environmental violence on cognitive performance (Aizer, 2007; Sharkey, 2010; Sharkey et al., 2012; McCoy, Raver, and Sharkey, 2015).

In this literature homicides are typically conceptualized as shocking events that generate anxiety and stress in children, diminishing their ability to focus on the test and hurting their performance. This mechanism is plausible given that violence –especially deadly violence– is rare in most American neighborhoods. The overwhelming majority of violence in the United States is related to 'street crime' and is heavily concentrated in pockets of disadvantaged and racially segregated neighborhoods or streets/corners within them (Sampson, 2012; Sampson and Wilson, 1995). Middle-class and wealthy neighborhoods rarely experience any violence at all. When violence takes place, most people expect the police and other criminal justice agencies to restore public safety, partly because these agencies enjoy high average levels of legitimacy and public trust, serious misconduct and corruption is rare, and people in general comply with their commands (Skogan and Meares, 2004; Tyler and Huo, 2002).

But in Latin America violence has distinct features that make it more pervasive and corrosive. Criminal justice agencies, governmental institutions, and society at large also perceive and respond to it in different ways, with potential implications for how violence shapes children's cognitive performance. Crime and deadly violence are not experienced as rare events, but as normal aspects of daily life (Davis, 2006; 2018). This is the result of high average levels of violence in the region and how violence has been densely interwoven with organized crime and organized armed groups (e.g., militias, paramilitary groups), politics, and civic unrest for decades (Auyero, 2007; Villarreal and Yu, 2017). Moreover, citizens overwhelmingly perceive criminal justice agencies as ineffective, illegitimate and corrupt and there is little support for the rule of law (Uildriks, 2010; Ungar, 2009). Conversely, there is widespread support for vigilantism stemming from the extended belief that people can only rely on themselves and those close to them to prevent victimization (Nivette, 2016).

In this chapter I study the relationship between environmental violence and cognitive performance in a Latin American country, beyond the traditional site of this type of research – large American cities. I argue that violence in Latin America has become normalized and that this has two important implications for children's cognitive performance: 1) children are desensitized to violence and; 2) children learn how to be vigilant as a coping mechanism to avoid victimization. The short-term consequence of these adaptive behaviors is that children recruit fewer cognitive resources to inhibit the emotional distraction represented by violent events and can concentrate more of these resources in whatever task is at hand, including cognitive tests. In general, this means that in this context children's cognitive performance should increase as environmental violence increases. However, desensitization can also lead to emotional numbing and despondency, whereas vigilance can become hypervigilance, a state of heightened anxiety that can lead to hyperactivity, chronic stress and exhaustion (American Psychiatric Association, 2013). This result is especially likely if the quantity and the gruesome nature of environmental violence become overwhelming and unmanageable. In this case violence should have a negative impact on children's cognitive scores. In putting forth this argument, I build on the Latin American literature on violence and the psychological body of work on desensitization and adaptation to violence exposure.

Based on this theoretical framework, I analyze the association between environmental violence and children's cognitive skills before and during the Mexican 'War on Organized Crime' (WOC). Violence during the WOC was not only extreme in terms of its quantity, but also in terms of its viciousness and brutality precisely because it resulted from confrontations between the army and DTOs and other organized armed groups across large regions of the country (Dell, 2015; Villarreal and Yu, 2017).

My findings show an inverted U-shape impact of violence on the cognitive skills of children, consistent with the theoretical expectations described above: as homicide rises cognitive scores also increase, but there is an inflection point in the level of homicides beyond which cognitive scores decrease substantially. Homicide levels beyond said inflection point are associated with the most extreme violence derived from the Mexican armed conflict. In these places, children are more likely to experience emotional numbness, hopelessness and hypervigilance –all associated with post-traumatic stress symptoms– that hinder their ability to focus on the cognitive test. Contrarily, one of the short-term side effects of the adaptive responses (i.e., desensitization and vigilance) of children living in places with homicide levels just before the inflection point is that they are more attentive and more able focus on the cognitive test. Supplemental analyses show that these results are robust and lend credibility to the main assumptions built into the research design. Further analyses render evidence that supports the posited mechanism. Although these analyses do not provide an exhaustive and precise test of the theoretical framework presented in this chapter, they do provide *prima facie* support for it and for a more complex relationship between environmental violence and cognitive performance than that uncovered by previous research.

Violence in Mexico and Latin America

Numerous scholars have suggested that crime and violence have become 'normal' or 'routine,' an important aspect of every day life in Latin America (e.g., Altman et al., 2018; Auyero and Berti, 2015; Davis, 2018; Moser, 2004; Moser and McIlwaine, 2006; Schepper-Hughes, 1992). The normalization of violence is a pathological adaptation that entails moral disengagement, manifested in attitudes and ways of thinking that disregard, minimize, justify, and misrepresent violence, while often vilifying and dehumanizing its victims (Bandura et al., 1996). In Latin America, this adaptation is the result of widespread and extreme violence largely brought about by political and organized crime power dynamics that have remained unchecked due to the state's inability to maintain the rule of law. In this context, as one prominent scholar puts it

“Violence becomes all-encompassing, can come from anyone, is everywhere, and is enduring, and as such it becomes part of life” (Menjívar, 2017: xiii).

Violence has exploded in the last decades making the region the deadliest in the world. Latin America is home to 8 percent of the world’s population, but to a third of its homicides. Most surprisingly, 1 in 4 violent homicides globally take place in Brazil, Mexico, Colombia, or Venezuela (Muggah and Aguirre Tabón, 2018). Although there is substantial national and subnational variation in violence and crime rates, the shared experience of higher than average violence rates, poverty and exclusion, political and social unrest, and weak governments and criminal justice systems does suggest that the region as a whole has been thrown into an ‘age of insecurity,’ characterized by the erosion of social, political, and economic institutions (Davis, 2006).

The extreme violence experienced in Latin America is deeply rooted in the historical overlapping of politics, crime control, and organized crime, which casts violence as a natural aspect of the state-society relationship. Violence is an essential part of politics in Latin America in myriad ways, even when it is not openly political (Piccato, 2017). The state and political actors are often directly involved or complicit in criminal and violent enterprises, as the history of drug trafficking in Mexico shows (Astorga, 2001). State-sanctioned violence is routinely deployed illegally to punish and repress political adversaries and dissidents or to boast of *mano dura* (‘tough on crime’) policies and positions for electoral gain (Ungar, 2009). Conversely, state-sponsored violence is applied irregularly to benefit political allies or to avoid situations that could ignite social revolt (Auyero, 2007; 2015). Violence is also political in terms of the solutions that are proposed to resolve it. For instance, in 2010 over 50 percent of Mexicans approved of a military coup as a solution to control crime and violence in the country (Carey and Santamaría, 2017). Moreover, DTOs and other armed groups are often political actors, too, sometimes *de facto*, but on other occasions quite deliberately. Finally, violence is related to politics because it shapes –and it is shaped by– political discourse and collective representations of violence (Carey and Santamaría, 2017). All of these modalities of violence can be placed on a continuum, a 'gray zone' of politics and violence (Auyero, 2007). Even traditional 'street crime' can be positioned along this continuum, as it is almost always connected to one or several of these forms of violence.

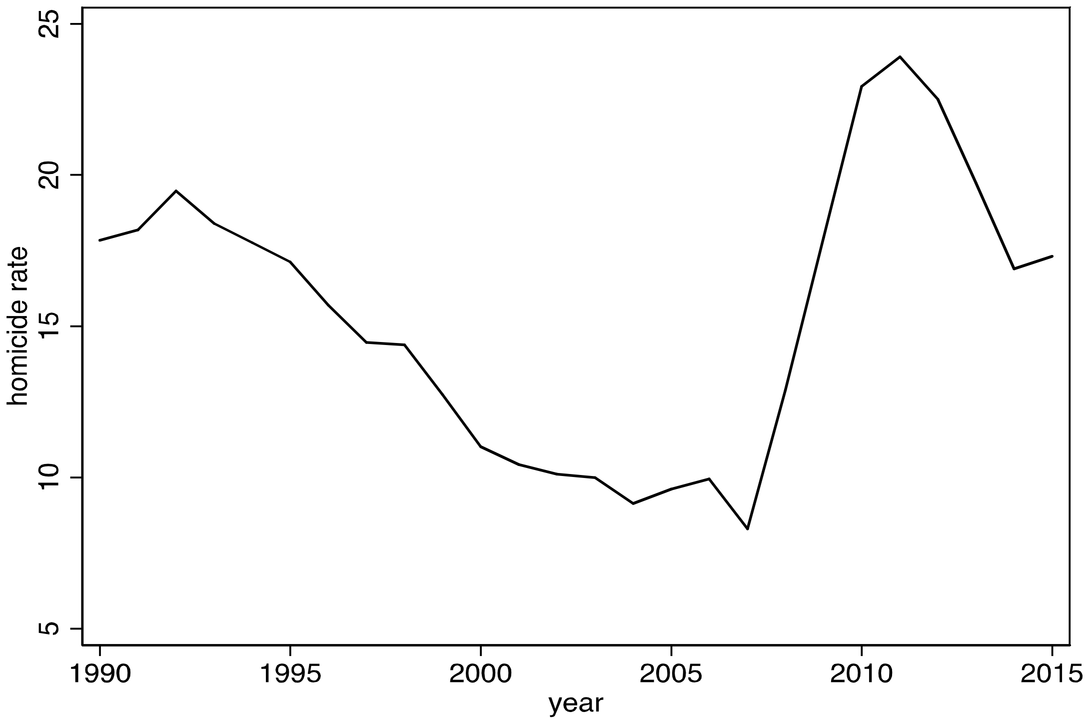
In Mexico, violence has been intertwined with politics and organized crime in one way or another since at least the Mexican Revolution a century ago. Up until the late 1980s, the political elite that ruled Mexico –affiliated with the Institutional Revolutionary Party (PRI)– had control of most criminal activity in the country, including drug trafficking, through a complex set of informal arrangements and rules that allowed drug trafficking and crime to flourish under the umbrella of politicians, local bosses (*caciques*) and police, and military commanders who benefited economically and politically, directly and indirectly, from this criminality (Astorga, 2001; Snyder and Durán-Martínez, 2009; Ríos, 2015; Villarreal, 2002). These informal arrangements dissuaded and limited violent and other predatory crimes (e.g., kidnapping, extortion), but homicidal violence was still high, particularly in the countryside where land disputes coupled with a weak state presence made violence more likely (Villarreal, 2004).

The late 1980s and early 1990s were marked by increased democratization and political strife, the loosening of traditional mechanisms of political control over dissidents and criminality, and the consolidation of crime and insecurity as key topics in the national debate due to rising crime and fear of crime (Davis, 2006; 2018; Ríos, 2015). The uneven democratization of the country meant that the PRI could no longer ensure the stability of the informal arrangement between the state and organized crime across levels of government or their continuity across administrations (Ríos, 2015). This is why regions that elected governors or mayors from the opposition often experienced more drug-related violence and other predatory crimes (Astorga, 2001; Villarreal, 2002).

The onset of the WOC at the end of 2006 marked a different stage in the relationship between politics and organized crime. The WOC was launched by incoming President Felipe Calderón to crack down on DTOs. Mayors and local leaders from the president's party (PAN, National Action Party) were the main supporters of the WOC (Dell, 2015), emphasizing the political bent of the strategy. Violence reached epidemic proportions during the WOC, with the national homicide rate of 8 homicides per 100,000 inhabitants in 2007 tripling by 2011 (see Figure 1.1) and some regions experiencing more violence than many war zones (Lessing, 2015: 1487).

In addition to high levels of violence, the type of violence characteristic of the WOC differs from the violence of traditional 'street crime' in another substantial way that highlights the connections between politics and violence in Mexico. Violence during the WOC was the result of confrontations between and amongst the army and organized armed groups

Figure 1.1 National homicide rate per 100,000 (Mexico, 1990-2015)



NOTE: Author's elaboration with data from Mexico's statistical agency (INEGI).

(paramilitary groups, militias, *autodefensas*, drug-trafficking organizations). There was considerable fluidity between these groups, too, reinforcing the notion of a 'gray zone' of politics and violence. For instance, members of an elite army unit were the original members of the *Zetas*, one of the deadliest DTOs (Shirk and Wallman 2015), and *The Knight Templars* –another notorious DTO– portrayed itself as an *autodefensa* to control crime and violence and protect communities in the state of Michoacán (Felbab-Brown, 2015). At different times these groups infiltrated each other and they also used similar tactics, armament and technology, and even military uniforms, which *de facto* made them indistinguishable from each other (Menjívar, 2017).

Violence during the WOC often involved high-caliber weaponry (e.g., assault and anti-armor weapons, grenades, anti-aircraft missiles and armored Humvees), military-style tactics, high-impact targets (e.g., mayors and other politicians, journalists, law enforcement officers) and the deployment of commandos across large swaths of territory. Much of the violence was also aimed at intimidating and terrorizing rival DTOs, the government and the general public, which is why it was often gruesome (e.g., beheadings, dismemberments, signs of torture), displayed openly (e.g., corpses left in public places or hanging from bridges, street gun battles) and produced to convey specific messages (e.g., corpses left with *narco*-messages) (Ríos, 2015: Shirk and Wallman, 2015).

The connection between politics, violence, and organized crime implies a tenuous or nonexistent rule of law. The most palpable manifestation of this is the inefficient, corrupt, and unfair criminal justice systems in the region (Ungar, 2009). Particularly in Mexico, these agencies are commonly "influenced by specific power constellations within society, rather than based on an impartial, just application of the rule of law to all" (Uildriks, 2010: 189). With reason, citizens are overwhelmingly distrustful of them (Bailey, 2009; Nivette, 2016) and often prefer to rely on themselves and their communities to cope with violence. In places with high violence and crime rates, people devise numerous strategies to protect themselves, such as traveling in groups, tightening supervision of their children and teaching them how to avoid victimization, changing their routines and movements in public space, and using private security systems (Auyero, 2015; Villarreal, 2015).

One important modality of these strategies was vigilantism, including its most extreme manifestation –lynching. Vigilantism and lynching are common in Latin America and Mexico specifically, where some of these practices have deep historical roots (Santamaría, 2017). The high prevalence of vigilantism and its widespread support in the region has been connected to perceived institutional illegitimacy, victimization, and punitive attitudes (Nivette, 2016), reinforcing the conclusion that citizens often prefer to take matters into their own hands on security and crime prevention issues.

Environmental violence and cognition: Towards a general framework

Current research on environmental violence and cognition

A growing body of work has examined the connection between environmental violence and children's outcomes. Most of it has concentrated on school performance and educational achievement (e.g., Beland and Kim, 2016; Brown and Velásquez, 2017; Burdick-Will, 2013; 2016; Caudillo and Torche, 2014; Gershenson and Tekin, 2015; Harding, 2009; Jarillo et al., 2016; Michaelsen and Salardi, 2018; Monteiro and Rocha, 2017; Sharkey et al., 2014), but a few studies have analyzed how environmental violence affects cognitive performance (Aizer, 2007; Sharkey, 2010; McCoy, Raver, and Sharkey, 2015). In general, both research streams find that environmental violence has a detrimental effect, although in the case of cognitive performance this effect is short-lived (one or two weeks) (Sharkey, 2010; McCoy, Raver, and Sharkey, 2015).

One key mechanism posited to explain the association between violence and cognition is that violence generates anxiety and psychological distress in guardians and children, which undermines the latter's impulse control and capacity to focus (Burdick-Will, 2013; 2016; Sharkey et al., 2012; Sharkey et al., 2014; Gershenson and Tekin, 2015). According to this reasoning, deadly violence is a shocking event and one of the many stressors to which children and families could be exposed in their daily lives, such as family deaths or negative economic shocks (e.g., job loss) (Margolin and Gordis, 2000; Foster and Brooks-Gunn, 2009; Sharkey, 2018).

However, these studies have been conducted almost exclusively in large American cities (Los Angeles, Chicago) (e.g., Aizer, 2007; Sharkey, 2010; Sharkey et al., 2012; McCoy, Raver, and Sharkey, 2015). This is important because homicides and violence are unequally distributed across American neighborhoods along socioeconomic and racial lines. Homicides are rare in middle-class and wealthy neighborhoods, but prevalent in some neighborhoods with concentrated disadvantage where 'street crime,' local gangs, and drug trafficking make violence more likely (Sampson, 2012; Sampson and Wilson, 1995). Due to segregation, people who do not live in these neighborhoods are unlikely to experience, witness or sometimes even find out about violent events, even in the deadliest American cities.

This unequal experience with crime is reinforced by criminal justice agencies. Police presence can be overwhelming in poor and racially segregated neighborhoods where it is common for community members –especially young males– to be entangled with the criminal justice system (Goffman, 2014; Rios, 2011; Stuart, 2016). In these circumstances, people might distrust the police and try to avoid any contact with them. But most people –particularly outside of these communities– trust the police and other criminal justice agencies and see them as legitimate institutions fulfilling their role to protect citizens and restore public safety (Skogan and Meares, 2004; Tyler and Huo, 2002).

In general, deadly violence can be reasonably conceptualized as shocking in American cities, that is, as discrete events that disrupt the regular functioning of communities. People generally believe that criminal justice agencies react accordingly, restoring this regular functioning by punishing the aggressors and preventing new transgressions, and this is often the case. But the experience of crime in Latin America is different. Children living in places where violence is normal and with little institutional support might react differently to violence, with implications for cognition. This suggests that research on environmental violence and cognitive performance could be exposing a limited range of relationships and mechanisms.

Environmental violence and cognition in Latin America: alternative mechanisms

Children are likely to become desensitized to violence when it is seen as a normal aspect of everyday life, as is the case in Latin America. Desensitization or habituation consists of the decreased response to repeated or prolonged applications of a certain stimulus (Thompson and Spencer, 1966). A robust literature based on experimental research has linked violence in video games and other media to aggressive thoughts and behavior, angry feelings, and decreased empathy and prosocial behavior through desensitization (e.g., Bartholow, Bushman and Sestir, 2006; Engelhardt et al., 2011; Gentile et al., 2016; Stockdale et al., 2017). Because of desensitization, people that have been exposed to violence need to recruit fewer neural resources to inhibit their emotional reactions when further exposed to violence (Stockdale et al., 2017). They are also less physiologically aroused, measured by heart rate, galvanic skin response, and cortisol levels (Carnagey, Anderson and Bushman, 2007; Di Tella et al., 2019).

These findings are not confined to laboratory settings. Research on community violence in the United States has confirmed that desensitization is a common response for children and youth living in highly violent environments (Cooley-Quille and Lorion, 1999; Gaylord-Harden et al., 2017; Ng-Mak et al., 2002; 2004). This work shows curvilinear relationships between exposure to community violence and several outcomes, including depression and sleep deprivation, pointing to complex influences of environmental violence operating through desensitization.

Experimental research has also linked desensitization or habituation to better cognitive functioning. In particular, individuals who were previously victimized or exposed to violence perform better in cognitive tests than those who were not, after being further exposed to violence (Di Tella et al., 2019). The former individuals can more easily and efficiently keep their emotions in check when administered the test and deploy more cognitive resources to focus and complete the test. Hence, the results from experimental and observational research support the conclusion that desensitization is a common response to repeat or prolonged exposure to both real and fictional violence and that this desensitization enables individuals to be calmer and more focused when faced with more violence, which translates to better cognitive performance.

The normalization of violence and its consequent desensitization do not imply that individuals stop worrying about violence. To the contrary, increased violence heightens vigilance because the possibility of victimization becomes more real. Vigilance is the capacity for sustained concentration and alertness to stimuli (Warm, Parasuraman, and Matthews, 2008) and it is necessary to navigate threatening and potentially dangerous interactions and situations and avoid victimization, especially for those that feel that they cannot rely on criminal justice agencies. Thus vigilance is a key component in cognitive and behavioral adaptations that children and youth develop in dangerous contexts, such as those captured by the concepts of 'street wisdom' (Anderson, 1990) or 'street efficacy' (Sharkey, 2006). In disadvantaged, inner-city neighborhoods in the United States scholars have described how vigilance and strategizing help children and youth navigate the challenges posed by gangs and the expanded presence of the police, as well as by employers, landlords and other private and governmental actors assigned policing responsibilities (Anderson, 1999; Desmond and Valdez, 2012; Elliott and Reid, 2019; Goffman, 2014; Sharkey, 2006; Stuart, 2016).

Similar mechanisms have been found in Mexico but given the nature of violence in the country they are not confined to disadvantaged contexts but rather apply to whole cities and regions. In a Mexican metropolis (encompassing several municipalities) besieged by the WOC individuals constantly planned and discussed their movements through the city and strategized about how to avoid violence and crime (Villarreal, 2015). These 'logistics' forced people to process information, recognize patterns, and construct some rational course of action to survive and navigate the challenging environment. These included 'armoring' (closing off communities and whole cities with barricades, fences, walls and gates), 'camouflaging' (dressing down, trying to blend in, and making businesses look run-down to avoid kidnapping and extortion), 'caravaning' (traveling in groups of automobiles or on busses), and 'regrouping' (holding gatherings and public events in closed-off streets). In this and many other municipalities, people avoided going out, especially at night, and limited their children's movements, too (Altman, Gorman and Chávez, 2018; Villarreal, 2015). But children were bound to experience the consequences of extreme violence through their direct contact with the environment or through friends and family members. The also had to be vigilant and react appropriately to signs of violence and potential threats, such as run-down streets, public spaces, businesses, and schools; the presence of the military, DTOs and other organized armed groups, drugs, and guns; sporadic gun battles and other signs of conflict.

Considering the conditions under which desensitization and vigilance are adaptive or maladaptive is key to understand their consequences. Desensitization and vigilance might protect or harm children, depending on the specifics of the context and the scope of the assessment (Margolin and Gordis, 2000: 466). For instance, they might protect children in the short-term but prove detrimental in the long run, or they could be damaging overall but carry some favorable side effects or be beneficial at low levels but hurtful in high doses.

I argue that in the Latin American context, due to its history of violence normalization and weak institutional support, desensitization and vigilance help children cope and function in daily life when violence is manageable or falls within a 'normal' range, both in terms of its quantity and quality. In these environments, children are used to violence and hence better able to control their reactions to it, while remaining cautiously vigilant and exerting mental effort to identify relevant cues and avoid victimization without being extremely fearful or anxious. These factors lead to better cognitive performance through a short-term concentration effect that is transferred from such vigilance and attentiveness. This mechanism is akin to the notion of 'functional fear,' or the moderate worry about crime that prompts individuals to take precautions and prepare but does not disrupt their lives (Jackson and Gray, 2010). Worrying about crime and violence can motivate people to problem-solve, as numerous other worries can (Taylor and Stanton, 2007). In turn, this has beneficial spillover effects for test taking, especially if test measures children's problem solving and reasoning skills.

However, if environmental violence becomes overwhelming because of its frequency and brutality, desensitization can turn into emotional numbing and vigilance into hypervigilance, two known symptoms of post-traumatic stress disorder that make children feel hopeless, extremely anxious, and hyperaroused (American Psychiatric Association, 2013; Margolin and Gordis, 2000). Under these circumstances, children's impulse control and ability to focus on cognitive tests would be impaired, lowering their performance. I argue that this is what happened to children in places that received the brunt of the Mexican WOC and its extreme and gruesome violence.

Data limitations preclude me from precisely testing this theoretical framework, but my analysis explores the association between environmental violence and children's cognitive performance in a context where violence is normalized and the cognitive responses contained in this framework are plausible. My main results are consistent with this framework and additional analyses that indirectly examine the mechanism also support this conclusion. This should prompt more research along these lines.

Because my theoretical argument requires the analysis of children living in contexts with a wide range of environmental violence to be properly explored, this chapter differs in essence from the work of Brown and Velásquez (2017), the only piece of research that has addressed the relationship between violence and cognition in Mexico and Latin America. Their goal was to assess the impact of the WOC specifically –and not environmental violence in general– on the cognitive performance of teenagers and limited their sample to those between the ages of 14 and 17 at the time of the WOC, as this cohort was arguably more likely to be exposed to the violence. They could not detect a significant effect of homicide in the previous month on cognitive scores and argue that this result is unsurprising given the short-lived effect detected in previous work in the United States.

Data and measures

I combine survey data of children and their households before and during the Mexican WOC with official homicide statistics to understand the effects of environmental violence on children's cognitive assessments. These cognitive assessments, as well as the children and household controls used in the analyses, come from the Mexican Family Life Survey (MxFLS), which consists of three waves of data collected in 2002 (MxFLS-1), 2005-2007 (MxFLS-2) and 2009-20013 (MxFLS-3) in a joint effort by American (Duke, UCLA) and Mexican universities and other institutions, most notably INEGI, Mexico's National Institute of Statistics and Geography.

The baseline round (MxFLS-1) was representative of all Mexican households and it collected information on members of more than 8,400 randomly sampled households in 150 communities (Rubalcava and Teruel, 2013). A total of 16,635 children between the ages of 5 and 12 in these households were assessed and their socio-demographic information was taken from the child's supervisor. Over 90% (MxFLS-2) and 85% (MxFLS-3) of the original households were re-contacted in later waves. The sample also includes the new children within that age range in both the original households and new households formed by individuals in the original sample (Rubalcava and Teruel, 2013). This data set provides the most comprehensive source of information on crime, violence, and children's cognition in Mexico, and it also includes a rich set of socio-demographic characteristics of children and households. For these reasons it has been widely used to study the consequences of crime and violence (e.g., Brown and Velásquez, 2017; Villarreal and Yu, 2017) and related topics, such as migration (e.g., Nobles, 2013).

The outcome of interest is *cognitive performance*, which I measure using 18 items of the Raven's Colored Progressive Matrices, often considered the best instrument to measure *fluid intelligence* (Hunt, 2011: 46; Nisbett et al., 2012: 145). Fluid intelligence can be conceptualized as the problem-solving and reasoning skills based on logic operations (i.e., induction, deduction) that are in large part orthogonal to *crystallized intelligence*, or the knowledge and skills acquired through education and experience in domain-specific areas, like mathematics or English (verbal ability) (Nisbett et al., 2012; Pagani, Brière, and Janosz, 2017). I use a count of correct responses in the main analyses, but I also explore alternative operationalizations as robustness checks.

The main predictors are the *homicide count* and its *quadratic term* in the children's municipality[1] or state in the months prior to the cognitive test. These data are taken from vital statistics provided by INEGI and they are the standard data used in studies of violence in Mexico for two reasons (e.g., Brown and Velásquez, 2017; Caudillo and Torche, 2014; Villarreal and Yu, 2017). First, homicide is the most extreme violent crime and the most reliably measured in Mexico and abroad (Mosher, Miethe and Hart, 2011; Shirk and Wallman, 2015). Second, homicides capture the existence and intensity of the WOC because most of the violence after 2007 was due to the armed conflict and its gruesomeness was highly correlated with homicide levels, meaning that homicide counts are the best proxies available for both the quantity and nature of deadly violence in Mexico (Shirk and Wallman, 2015). I use both municipal- and state-level homicides to capture the extra-local nature of much of the violence in Mexico.

I also include an array of individual and household variables that previous theory and empirical findings suggest could be connected to cognitive performance and homicide levels. I control for children's age, gender, ethnicity (a binary for indigenous status), and a set of education-related factors (education level, whether the child currently attends school, has ever attended school, or has repeated a school year). I also include controls for whether the child was in an accident in the last few days and the number of ailments that she/he has had in the same period.

[1] The municipality is the basic political and administrative territorial division in Mexico. Some municipalities have large territories that are often sparsely populated and enclose several towns and/or cities; others have small territories but are densely populated and cluster to form large metro areas, such as Mexico City, Guadalajara, Monterrey (INEGI, 2010).

At the household level, I include the number of children in the household (less than 15 years old) and a set of variables that indicate if the household has indoor plumbing, solid (i.e., not dirt) floors, private toilet, electricity, more than two people per room, at least one adult earning more than 2 minimum wages per day, at least one adult with a middle-school education or higher, at least one member that identifies as indigenous or speaks an indigenous language, and at least one member currently living in the United States. I also include binary variables for household shocks (deaths, hospitalizations, unemployment or business failure, loss of home or business due to a natural disaster, and crop and livestock loss), municipality change between waves, female-headed household, and victimization, the latter operationalized as personal (kidnapping, harassment/sexual abuse, robbery/assault, and bodily injury) or household (breaking and entering home, business or plot/land) victimization in the previous two years. Finally, I control for size of the community.

I exclude 3.4 percent of observations with missing data on any of these variables and I drop an additional 46 observations from municipalities without within-municipality-by-wave variation in homicide counts, a variation that is essential in my research design (see below). The primary analytical sample is comprised of 16,021 student-wave observations distributed in 441 municipality-wave contexts. Summary statistics of the variables in the main analyses are reported in Table 1.1.

Table 1.1 Descriptive Statistics

Variable	Mean or %	SD	Range
Outcome			
Cognitive score	10.94	3.76	0-18
Predictors			
Homicides (municipality)			
1 month	3.27	8.04	0-101
2 months	6.48	16.09	0-189
3 months	10.19	25.07	0-269
Homicides (state)			
1 month	47.17	45.34	0-278
2 months	94.02	89.25	0-514
3 months	140.66	133.24	0-768
Individual controls			
Age	8.64	2.26	5-12
Gender (male)	49.50%		
Education (none or pre-k)	19.99%		
Education (elementary)	76.45%		
Education (secondary)	3.56%		
Attends school	96.11%		
Ever attended school	97.28%		
Repeated grade	11.43%		
Indigenous	13.49%		
Accident	1.27%		
Sickness	1.67	2.33	0-15
Household controls			
Floors	85.19%		
Sewage	54.02%		
Toilet	69.53%		
Electricity	97.75%		
Indigenous	25.26%		
Female headed	19.52%		

Table 1.1 (Continued)

Adults middle school	42.26%		
Adults minimum wage	43.29%		
2 people per room	31.57%		
Children	2.86	1.41	1-13
US migration	37.28%		
Municipality change	0.51%		
Crime victimization	0.03	0.11	0-2.25
Shocks	26.23%		
Wave 1	38.19%		
Wave 2	32.95%		
Wave 3	28.86%		
Year			
2002	38.19%		
2005	25.10%		
2006	7.67%		
2007	0.17%		
2009	17.68%		
2010	9.52%		
2011	1.35%		
2012	0.17%		
2013	0.12%		
Month			
January	5.13%		
February	2.16%		
March	2.52%		
April	13.35%		
May	21.62%		
June	17.39%		
July	8.08%		
August	10.37%		
September	5.79%		
October	6.06%		
November	4.46%		
December	3.08%		

Table 1.1 (Continued)

Population (locality)	
0-2,499	45.49%
2,500-14,999	11.04%
15,000-99,999	9.77%
100,000 or more	33.71%

NOTE: N = 16,021 (children-wave).
ABBREVIATION: SD = standard deviation.

Estimation strategy

I follow recent work that capitalizes on the relative timing of children´s cognitive or educational assessments with respect to homicidal events in the same environment (Sharkey, 2010), as well as novel research that has explored the consequences of violence in Mexico (Brown and Velásquez, 2017; Jarillo et al., 2016; Michaelsen and Salardi, 2018). In the MxFLS, it took surveyors three months on average to assess all the children in a given municipality in each wave, but often a few more (mean=2.97; s.d.=4.37). The number of months necessary to conduct all the assessments increased in MxFLS-2 and MxFLS-3, due to the extra time and effort needed to locate and interview panel and new households. Therefore, children were tested in the same municipality and wave across different months. This allows me to compare the cognitive scores of children living in the same municipality at each wave, but that nevertheless had experienced different homicidal patterns at the municipal and state levels in the previous months due to the month in which they took the cognitive test. Formally, I estimate two sets of regression models to predict children's cognitive scores. The first models are linear regression models with municipality-by-wave fixed effects and homicides aggregated at the municipality level:

$$y_{ijwtm} = \beta_0 + \beta_1 Hom_{jm} + \beta_3 \boldsymbol{IC}_{iw} + \beta_4 \boldsymbol{HC}_w + \alpha_t + \alpha_m + \alpha_{jw} + \mu_{ijwtm} \quad (1)$$

$$y_{ijwtm} = \beta_0 + \beta_1 Hom_{jm} + \beta_2 Hom_{jm}^2 + \beta_2 \boldsymbol{IC}_{iw} + \beta_3 \boldsymbol{HC}_w + \alpha_t + \alpha_m + \alpha_{jw} + \mu_{ijwtm} \quad (2)$$

where y_{ijwtm} is defined as the cognitive assessment score for child i, located in municipality j, in wave w, in year t, and month m; Hom_{jm} and Hom_{jm}^2 are the homicide count and its quadratic term, respectively, in municipality j in the m month(s) prior to the cognitive assessment; $\boldsymbol{IC}_{iw}$ is a vector of children characteristics and $\boldsymbol{HC}_w$ a vector of household characteristics; α_t and α_m are calendar year and month fixed effects, respectively; α_{jw} is the municipality-by-wave fixed effect, and μ_{ijwtm} is the idiosyncratic error term. I use clustered errors at the municipality level to account for the loss of independent variation in the error terms. The second set of models are the same as Models (1) and (2) but with homicide counts aggregated –and standard errors clustered– at the state level.

Given these model specifications, my estimates of β_1 in Model (1) represent the linear change in test scores related to a one-homicide increase in the municipality or state of residence in the month(s) before the cognitive test, whereas estimates of β_1 and β_2 in Models (2) represent the curvilinear impact of the number of homicides in the municipality or state in the month(s) prior to the cognitive assessment. These estimates are obtained by comparing the scores of children that were tested in the same municipality and survey wave, but in different months. The models are designed to estimate the short-term impact of environmental violence on cognitive performance and thus I use recent homicide counts (from one up to three months) in different specifications.

This approach helps allay concerns about biased estimates because it eliminates systematic variation stemming from numerous sources, including seasonal fluctuations, year-to-year changes and, most importantly, unobserved and time-invariant municipal characteristics. These characteristics, which include demographic and structural factors such as poverty and inequality, quality of law enforcement agencies and schools, and crime control and other municipal policies, are assumed to remain constant between assessments in a given municipality-wave. Two other key assumptions of this research design are that cognitive ability is not a predictor of the timing of the cognitive tests in the same municipality and wave and that homicide levels after the test do not have an effect on cognitive scores. I discuss these assumptions in more detail in the Results section and provide evidence to support their plausibility.

I examine all the children that were tested from the ages of 5 to 12. This decision is based on several considerations. The test that was administered to 5-12 year-olds differs substantively from the one taken by those older than 12. Any test design effect would be difficult to disentangle from the true effects of homicide levels. More substantively, although perhaps less exposed to violence than adolescents, children might be more sensitive to environmental violence given the developmental reasons explained before.

Results

Main analyses

I present the results from the main analyses in Tables 1.2 and 1.3. Homicides are aggregated over one month, two months and three months prior to the cognitive test and each term is then introduced in separate models.[2] This is done for both the municipality (Table 1.2) and state (Table 1.3) levels. Models 1, 3, and 5 provide no evidence of a linear relationship between homicides and cognitive performance, as the corresponding coefficients are small and far from statistical significance.

Table 1.2 Fixed-Effects Models of Municipal Homicides Predicting Cognitive Scores

Municipal homicides	(1)	(2)	(3)	(4)	(5)	(6)
t - 1	-0.009	0.035				
	(0.014)	(0.024)				
t - 1 (sq)		-0.00056**				
		(0.0002)				
t - (1 + 2)			-0.003	0.027*		
			(0.006)	(0.014)		
t - (1 + 2) (sq)				-0.0002***		
				(0.00007)		
t - (1 + 2 + 3)					-0.001	0.021**
					(0.003)	(0.009)

[2] Aggregating homicidal events across months or years is a common strategy in criminological research (see, e.g., Kirk and Papachristos, 2011). In the Appendix I present the quadratic models with homicides in each month introduced as separate terms. The pattern of results is substantively the same as that presented in the main findings but some of the coefficients are not statistically significant, most likely because homicides are highly correlated month-to-month. The variance inflation factor (VIF) for these terms confirms that multicollinearity is a problem with these models.

Table 1.2 (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)
t - (1 + 2 + 3) (sq)						-0.00007***
						(0.00003)
P-value for U-test		0.074		0.033		0.014
P-value for F-test		0.000		0.002		0.003
R^2	0.31	0.31	0.31	0.31	0.31	0.31
N	16,021	16,021	16,021	16,021	16,021	16,021

NOTE: Results presented are coefficients with standard errors clustered at the municipal level in parentheses. All the models include municipality by wave, calendar year, and month fixed-effects and control the individual and household controls in Table 1.1.
*** p<0.01, **p<0.05, *p<0.10 (two-tailed tests).

Conversely, Models 2, 4, and 6 provide evidence of an inverse U-shaped relationship. The coefficients in these models represent the impact of homicide and homicide squared on cognitive performance and they show a consistent pattern of increased cognitive performance as environmental homicides increase moderately (positive estimate on linear term) but decreased cognitive scores when homicide levels are high (negative coefficient on quadratic term). The U-tests test the composite null hypothesis that the relationship between homicides and cognitive performance is monotone or U-shaped (Lind and Mehlum, 2010).[3] These tests are statistically significant, meaning that the null hypothesis can be rejected at the p<0.05 significance level.

[3] Assessing statistical significance for the coefficients on homicide and homicide squared individually or using a joint test of significance (e.g., F-test) is not sufficient to confirm the existence of an inverted u-shape relationship. The reason for this is that the inflection point might be too close to the most extreme value of the homicide distribution. The U-test uses the homicide distribution to confirm that the results are not driven by values outside the actual data range. It performs a significance test comprised of two ordinary t-tests, one for each side of the curvature formed by the relationship of interest, in this case cognitive scores and homicides (Lind and Mehlum, 2010).

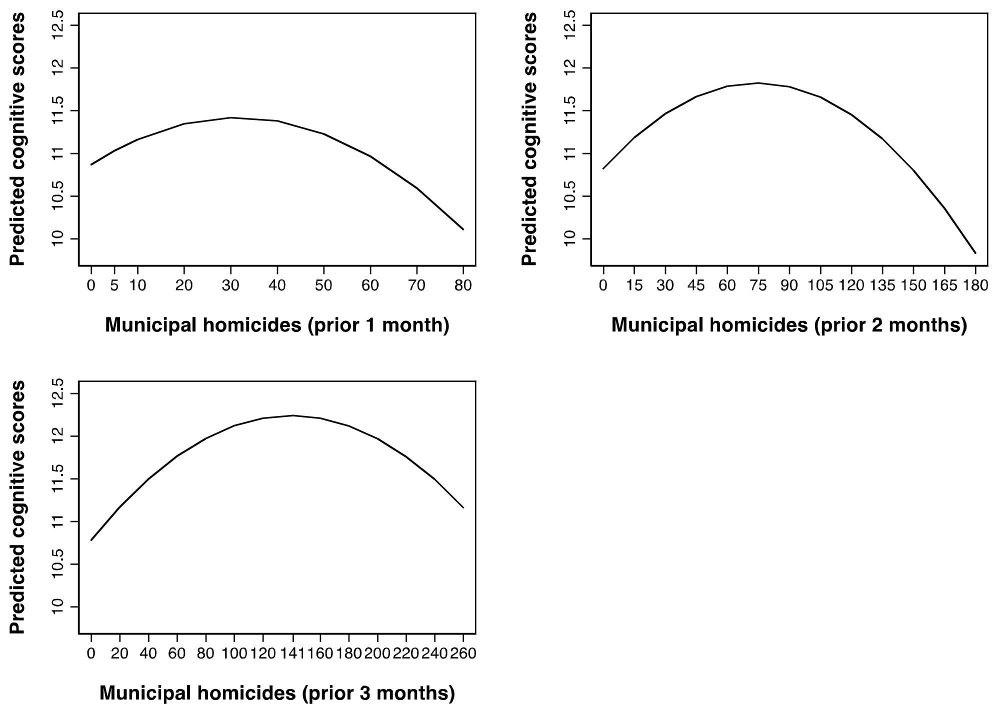
Table 1.3 Fixed-Effects Models of State Homicides Predicting Cognitive Scores

State homicides	(1)	(2)	(3)	(4)	(5)	(6)
t - 1	0.002	0.017**				
	(0.003)	(0.006)				
t - 1 (sq)		-0.00006**				
		(0.00002)				
t - (1 + 2)			0.002	0.017***		
			(0.002)	(0.005)		
t - (1 + 2) (sq)				-0.00003***		
				(0.000009)		
t - (1 + 2 + 3)					0.0007	0.010***
					(0.001)	(0.003)
t - (1 + 2 + 3) (sq)						-0.00001***
						(0.000003)
P-value for U-test		0.009		0.004		0.001
P-value for F-test		0.038		0.013		0.004
R^2	0.31	0.31	0.31	0.31	0.31	0.31
N	16,021	16,021	16,021	16,021	16,021	16,021

NOTE: Results presented are coefficients with standard errors clustered at the state level in parentheses. All the models include municipality by wave, calendar year, and month fixed-effects and control for the individual and household controls in Table 1.1.
*** p<0.01, **p<0.05, *p<0.10 (two-tailed tests).

Figures 1.2 and 1.3 depict the predicted cognitive scores obtained from the models with both the linear and quadratic homicide terms and the municipality and state homicides, respectively. They confirm that a rise from low to moderate levels of homicide at both levels of aggregation is positively associated with cognitive performance in children, but that very high levels are related to lower cognitive scores.

Figure 1.2 Predicted Cognitive Scores as a Function of Municipal Homicides

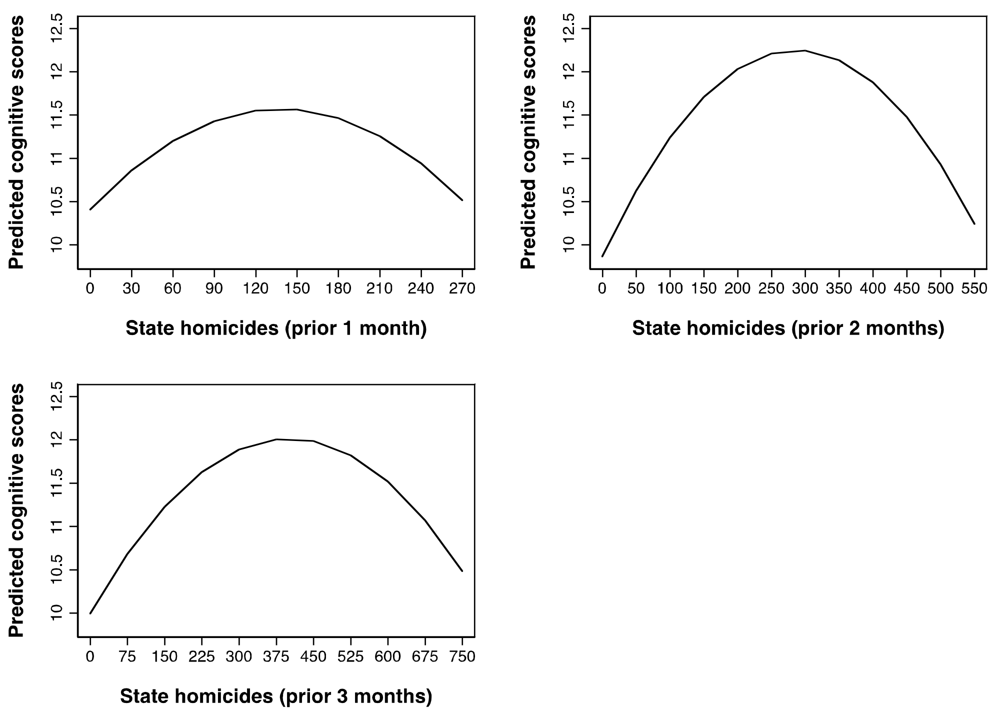


NOTE: Based on estimates of Models 2, 4 and 6 in Table 1.2, respectively.

A rise from 0 to 5 municipal events in the previous month is associated with an increase of 0.13 points in the cognitive test. A rise from 0 to 32 is associated with an increase of approximately half a point in cognitive scores. Almost 99 percent of the children analyzed lived in municipalities within this latter homicide range at the time of the cognitive assessment. Proportional rises in homicidal violence in the municipality two and three months prior to the cognitive assessment are associated with increases in cognition of 1 and 1.5 points, respectively. Increases in municipal homicides beyond this turning point are associated with a decrease in cognition of about 1 point for the most violent contexts one month before the cognitive test.

Similar increases and decreases are detected for homicides at the state level. These effects are modest in size given the distribution of cognitive scores (mean = 10.93; s.d. = 3.76). However, the fact that homicides have an impact despite being aggregated at large scales (municipality and state) is consequential because it speaks to the relevance of phenomena that might not be taking place in the immediate vicinity of where children live and develop. In turn, these results confirm the conclusion that violence in Mexico and its consequences are connected to extra-local phenomena related to political and organized crime dynamics.

Figure 1.3 Predicted Cognitive Scores as a Function of State Homicides



NOTE: Based on estimates of Models 2, 4 and 6 in Table 1.3, respectively.

These results are robust to numerous alternative model specifications. The OLS procedure assumes a Gaussian distribution for the outcome variable, which might not approximate well the data-generation process of cognitive scores. To examine if my results are sensitive to this assumption, I run the substantive analyses using the proportion of correct responses in the exam as the outcome variable and a generalized linear model that assumes a binomial distribution with a canonical link (logit). The results presented in the Appendix show a similar pattern. Results are also substantially the same if the analyses are carried out using a normalized operationalization of the outcome variable (by age and wave) (see Appendix) (Powers, 2011).

I also relax the parametric assumption regarding functional form and perform the main analyses using restricted cubic splines, a semiparametric technique that provides more flexibility (Harrell, 2010; Keele, 2008). The corresponding graphs presented in the Appendix suggest that a quadratic functional form is a reasonable approximation to the relationship between homicides and cognitive scores. The graphs with municipal homicides aggregated over one and two months show an initial dip in cognitive scores after which the association takes a distinctively quadratic shape. This dip might be due to idiosyncratic variation and could be the result of overfitting.

I also add two key control variables to the models. First, I include the average cognitive score of everyone in the household above 12 years old. These household members are subjected to many of the same influences as the children in the sample (including exposure to homicide levels) and are potential caregivers to the younger children that could influence their cognitive development. Second, I add a lagged dependent variable to construct a 'valued-added' model (Todd and

Wolpin, 2003). The pattern of results presented in the Appendix is similar to the pattern in the main findings.

Lastly, I perform three additional sets of analyses that I present in the Appendix. I first reproduce the main analyses without the children- and household-level controls to exclude the possibility that they could be blocking a potential pathway between homicide and cognitive performance, which would generate a spurious relationship between them (Elwert and Winship, 2014). There is no evidence of this. Secondly, I extend the main analyses by including all children and youths 18-year-old and younger. I add an indicator variable to control for the fact that teenagers older than 12 were tested using a related but different instrument and use the normalized cognitive scores as the outcome variable. Again, the results are robust. Lastly, I reproduce the main analyses using homicide rates per 1,000 inhabitants for one, two and three months prior to the test. The results are consistent, although some relationships are not statistically significant. This might be because homicide rates are quite sensitive to small increases in homicide events when the denominator (municipality population size) is also small (Slocum et al., 2013: 185). Including population size as a separate predictor renders substantively identical results as the main analyses (Appendix).

Assessing the plausibility of the research design

A core assumption of my research design is that cognitive ability is not a predictor of the timing of the cognitive tests in the same municipality or state and wave. It is possible, for instance, that children with more cognitive ability were systematically tested earlier than children with less cognitive ability for a variety of reasons. If this were the case, these children might be subjected to systematically different violence patterns than children with lower cognitive ability, biasing the estimates of the impact of homicides. I test for this possibility by employing similar models as those in the substantive analyses, but with month of the test in each municipality or state as the outcome and cognitive scores as the main predictor. The analysis presented in the Appendix shows no evidence that the cognitive scores predict the timing of the test.

However, some children- and household-level characteristics do systematically predict the month of the test. Children who were involved in an accident or sick recently were interviewed later, as well as children in households that changed municipalities between waves, most likely due to the fact these interviews had to be rescheduled. Children living in households with a relatively higher socioeconomic status were interviewed sooner, on average, as suggested by the significant (or marginally significant) coefficients on electricity, toilet, migration,[4] number of children, and female-headed households.[5] Households with this socioeconomic status might live in places that are easier to access or that might make the test taking easier for children, such as communities with electricity and paved roads. This suggests that there is no systematic test score heterogeneity between children that were tested in the same municipality or state across different months and that –although not fully random– the timing of the test is influenced mostly by pragmatic considerations that are controlled for in the main analyses.

[4] Migrant households often have better socioeconomic outcomes than non-migrant households due to remittances (Villarreal and Shin, 2008).

[5] Sewage is the only socioeconomic variable that predicts the opposite outcome. This might be because it is highly

A second key assumption is that the causal ordering of the analysis is correct. This entails that the homicide levels after the cognitive tests were administered should not affect the scores. I conduct placebo tests using similar methods but with homicides measured after the tests to assess this possibility. The analyses presented in the Appendix show that although one set of coefficients is marginally significant, the rest of the coefficients are insignificant.

Lastly, the main analyses also assume that a large but indeterminable set of municipal characteristics are constant and have a constant association with children's cognitive scores within municipality-wave. This is a reasonable assumption given that on average there was only a short period elapsed between assessments in each municipality-wave and most socioeconomic, political, and public security changes at this level develop slowly across time. However, especially for the second and third waves of data, a sizable minority of children was tested in the same municipality and wave across a long period that sometimes spanned years. To justify this assumption and make sure that the cognitive scores of these children are not driving the results, I restrict the sample to children who were tested within 6 and 12 months from the initial month of testing in a given municipality-wave. These analyses are also included in the Appendix and show that the pattern of results is similar, albeit coefficients are much larger with these restricted samples.

Exploring the underlying mechanism

I have argued that the impact of environmental violence on cognitive scores operates through the child's attentiveness –or lack thereof– and (in)ability to focus. Although data constraints do not allow me to examine this mechanism directly, I am able to analyze how much time the child spent on the test. This is related to attention and impulse control because research in the United States has shown that lower attention and impulse control in children as a result of environmental violence translates to faster completion of tasks, in addition to lower performance in tests (McCoy, Raver and Sharkey, 2015; Sharkey et al., 2012). Children need to sustain their focus and effort for some amount of time to answer cognitive tests and violence hinders that capacity.

Table 1.4 Fixed-Effects Models of Municipal Homicides Predicting Time to Complete the Cognitive Test

Time test	Municipal			State		
	(1)	(2)	(3)	(1)	(2)	(3)
t - 1	-0.019			-0.018**		
	(0.022)			(0.008)		
t - (1 + 2)		-0.053***			-0.015**	
		(0.020)			(0.006)	
t - (1 + 2 + 3)			-0.035***			-0.012***
			(0.013)			(0.004)
R^2	0.12	0.12	0.12	0.12	0.12	0.12
N	16,011	16,011	16,011	16,011	16,011	16,011

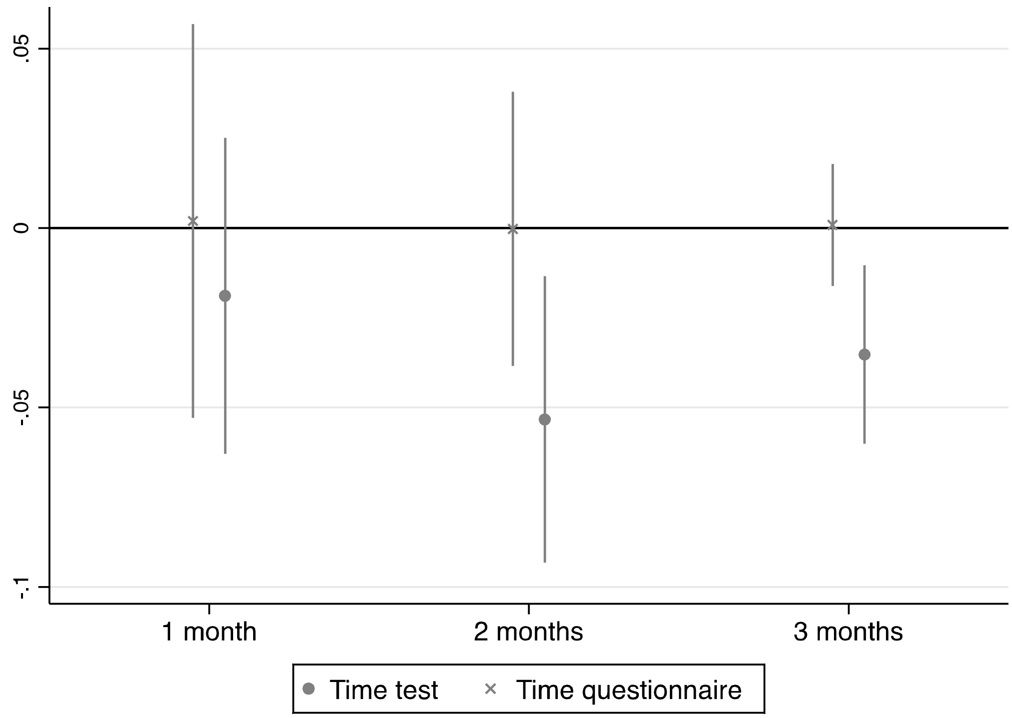
NOTE: Results presented are coefficients with standard errors clustered at the municipal- and state-level in parentheses, depending on the analysis. All the models include municipality by wave, calendar year, and month fixed-effects and control for the individual and household controls in Table 1.1.
*** p<0.01, **p<0.05, *p<0.10 (two-tailed tests).

Based on this research, I hypothesize that children living in environments of extreme violence should have much lower completion times. But higher attention due to desensitization and vigilance in moderately violent places would also decrease the amount of time spent on the test, but not as much as in extremely violent places.

To examine this argument, I use the same models as in the main analyses but with time spent on the test as the outcome variable and linear homicide predictors. As Table 1.4 shows, environmental violence is a negative and statistically significant predictor in most specifications. The size of the coefficients indicates that increases in homicides in the municipality or state predicted a reduction in the amount of time to complete the test of 0.012 to 0.054 minutes depending on the estimate. For instance, the predicted values indicate that children tested in a place with 20 municipal homicides in the previous 3 months –a moderately violent context– completed the test in 12.6 minutes, a small decrease from nonviolent contexts (13.28 minutes). But children in extremely violent municipalities finished in about half that time (5-6 minutes). In combination with the main findings, these results suggest that children who performed better as homicides increased moderately were able to focus more on the test and this slightly shortened the time that it took them to finish. But for those children living in places where violence increased dramatically the predicted amount of time that they spent on the test was cut drastically, suggesting that they could not maintain their focus on the test for long enough to improve their performance.

It is possible that the interviewer or the child's supervisor –and not the child– were the ones in a hurry to finish the testing. If the interviewer or the supervisor were concerned about environmental violence, they could put pressure on the child to finish sooner or even cut the test short. To rule out this alternative mechanism, I perform the same analyses but using a measure of

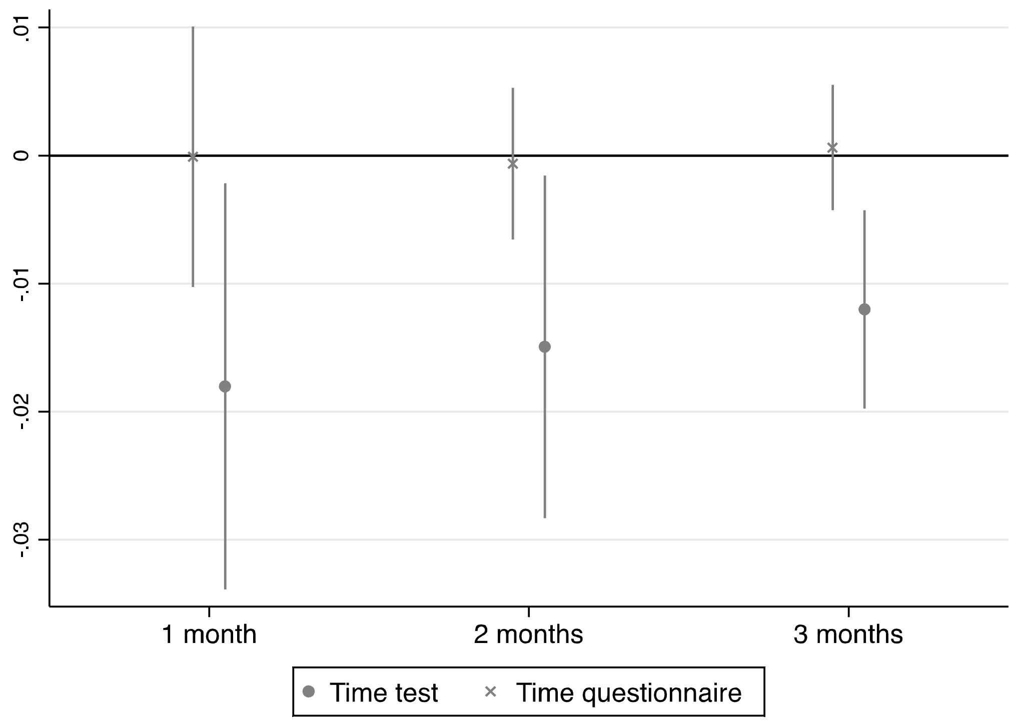
Figure 1.4 A Comparison of Estimates of Municipal Homicides Predicting Time to Complete the Cognitive Test and the Supplemental Questionnaire



NOTE: Circles and crosses with lines represent point estimates with standard errors clustered at the municipal level and 95 percent confidence intervals.

the time spent on the supplemental questionnaire as the outcome. This questionnaire includes information on the child's education, health, socioeconomic profile, and other characteristics and it was applied to the child's supervisor, typically the mother, father or other adult household member. If the interviewer, the supervisor or both were in a rush, then I should be able to detect a negative relationship between homicides and how long it took to fill out this supplemental questionnaire, just as I did with the time to complete the cognitive test. Figures 1.4 and 1.5 compare these two sets of estimates. The homicide coefficients in the models with time to complete the questionnaire are small and far from statistical significance across all specifications, which strongly suggests that environmental violence impacts cognitive scores through children's attentiveness and not this alternative mechanism.

Figure 1.5 A Comparison of Estimates of State Homicides Predicting Time to Complete the Cognitive Test and the Supplemental Questionnaire



NOTE: Circles and crosses with lines represent point estimates with standard errors clustered at the state level and 95 percent confidence intervals.

Discussion

A growing body of work indicates that violent environments are detrimental for children's cognitive performance, in large part because deadly violence shocks and stresses children, preventing them from focusing on tests. Thus far, this research has explored a restricted range of environments, namely large American cities. However, whether violence is shocking depends on how children perceive it, their context, and the quantity and type of violence, which is why it is important to extend the type of setting where the connection between environmental violence and children's cognitive performance has been studied.

In this chapter I do so by focusing on Mexico. I argue that violence in this country and across Latin America has become normalized due to widespread and extreme violence largely brought about by political and organized crime power dynamics that have continuously undermined the rule of law. This normalization desensitizes children to violence while making them more vigilant to avoid victimization. In general, one of the consequences of these adaptive behaviors is that children are able to more easily ignore the violence happening in their surroundings and recruit more neural resources to focus on tests. But desensitization can also lead to emotional numbing and vigilance can turn into hypervigilance if the violence is too discomforting and becomes overwhelming and unmanageable, obstructing children's attention and their ability to focus.

Based on this theoretical framework, I analyze the impact of environmental violence on children's cognitive skills before and during the Mexican 'War on Organized Crime' (WOC). My findings suggest an inverted U-shape effect of violence on the cognitive skills of children, consistent with the theoretical framework: as homicide rises cognitive scores also increase, but there is an inflection point in the level of homicides beyond which cognitive scores decrease. I argue that in extremely violent places children are more likely to experience emotional numbness, hopelessness and hypervigilance –all associated with post-traumatic stress symptoms– that hinder their ability to focus on the cognitive test. Contrarily, one of the side effects of the adaptive responses (desensitization and vigilance) of children living in places with homicide levels just before the inflection point is that they benefit from a short-term concentration effect.

The theoretical innovation and novel findings in this chapter are possible in large part because of the context where it was developed, but they build on the American literature in interesting ways. Although the violence in disadvantaged and racially segregated neighborhoods in large American cities is different in scale and quality than the violence in Mexican contexts where the armed conflict erupted, these places share some similarities. In both, there is a high police and law enforcement (army, in the case of Mexico) presence and activity, but the population is generally distrustful of these agencies; violence and criminality largely stem from the activity of gangs and other criminal or armed groups (DTOs, paramilitaries, and militias in Mexico); random acts of violence can take place at any time; people often respond to this violence by strategizing or disengaging from the environment. Children living in these environments could reasonably be distressed, which could impact their cognitive scores by affecting their concentration. In this sense, my findings of a negative effect of environmental violence on cognitive performance in places with extreme violence are consistent with the findings from previous work.

However, my theoretical framework also accounts for how environmental violence would affect cognitive performance in places where violence –despite creating challenges for individuals– is not as dramatic and/or pervasive. In these places, violence heightens children's vigilance and pushes them to take precautions, but without overwhelming them. When children are tested in these circumstances, they benefit from a short-term concentration effect that is transferred from such vigilance and attentiveness, allowing them to have better cognitive functioning. As other types of moderate concerns, moderate worries about victimization and violence can even provide an incentive to perform high-order cognitive functions, such as information processing, pattern-recognition, and problem-solving. In turn, this can have beneficial spillover effects for test taking, especially if the test measures children's problem solving and reasoning skills. This theoretical framework would be especially applicable to countries in the Global South, where government corruption is common, the rule of law is not widespread, the schooling system is deficient, and employment opportunities are lacking. Individuals learn early on in these places that resourcefulness and creative thinking pays off, as this might have a large impact on life outcomes when individuals cannot consistently rely on institutional support or educational and employment opportunities.

My findings might seem to contradict research on Mexico and other Latin American countries that finds a negative effect of violence on outcomes closely related to cognition, such as school achievement or performance and standardized test scores (Brown and Velásquez, 2017; Caudillo and Torche, 2014; Jarillo et al., 2016; Michaelsen and Salardi, 2018; Monteiro and Rocha, 2017). But environmental violence could conceivably have a different relationship with cognitive tests measuring fluid intelligence than with other measures of domain-specific skills and knowledge typically acquired through formal education, such as math or verbal skills. Numerous pathways can connect violence with performance in these domains that could be unrelated with cognitive scores. For instance, environmental violence can decrease the likelihood that children attend school, either because parents prefer to keep them safe at home (Rosenblatt and DeLuca, 2012), because violence disrupts children's routes to school (Burdick-Will, Stein and Grigg, 2019) or it increases the likelihood of household financial hardship (Brown and Velásquez, 2017), which can push children out of school and into the labor market. Violence can also increase teachers' absenteeism and turnover (Jarillo et al., 2016; Monteiro and Rocha, 2017). These disruptions likely decrease formal learning in substantive areas of knowledge, but they might not affect the problem-solving and logical skills embodied in fluid intelligence in the same way.

Another important consideration is that although aggregating homicides at the municipality and state levels is consistent with the nature of violence in Mexico and with prior work on the topic (Villarreal and Yu, 2017), this design feature could also shape the results in theoretically interesting ways. At this broader level of aggregation, children might be less likely to be exposed to violence than in smaller contexts, such as neighborhoods. Children living in moderately violent residential environments that nevertheless are not exposed to violent events might react in ways that enhance their short-term concentration while avoiding the psychological brunt of these violent events. As violence in the broader area becomes extreme, exposure becomes more likely, which could distress children. Even if children avoid exposure, the intensity of this extreme violence would prove overwhelming, as in these places signs of violence are common and generalized fear, hopelessness, and hypervigilance might set in.

Future research should address some of the issues raised by this work that could not be fully addressed here due to data limitations. First, it is important to operationalize environmental violence at smaller levels of aggregation, such as neighborhoods or blocks, to compare it with the results provided in this chapter and the literature. Second, testing different types of environmental violence would also be a promising extension of this work. This could entail distinguishing among different types of homicide (e.g., homicides as a result of domestic violence vs. organized crime) or using different crimes (e.g., robbery, kidnapping). Finally, research can also test the mechanism posited here more directly by measuring attention and impulse control and examining how it varies with environmental violence, as work in the United States has done.

Social scientists have recognized the importance of residential environments in the wellbeing of children and have identified environmental violence as one of the main threats to this wellbeing. However, most of what we know about this issue comes from research conducted on a limited range of environments. As my work shows, expanding this range can lead to a more general theoretical and empirical understanding of these phenomena.

2

Environmental violence and weight outcomes in Mexican adults

Abstract

A growing literature suggests that violent environments contribute to excess weight, a pressing health issue worldwide. However, this research has been carried out almost exclusively in the United States and other developed countries, where both violence and excess weight concentrate in socioeconomically deprived and racially segregated communities. In contrast, in numerous developing countries violence is more widespread and intense, while excess weight can be disproportionately found in middle-class and wealthy households. In this chapter I hypothesize that in such contexts we should expect a *larger* average positive impact of violence on weight gain and a *stronger* association between violence and weight gain in people with higher socioeconomic status, young adults, and women. I assess these claims using data from before and during the Mexican 'War on Organized Crime' (WOC). My analyses improve upon many of the methodological, data, and measurement limitations of previous work and my findings lend support to the hypotheses put forth. In doing so, I leverage both the theoretical insights constructed in the traditional site of this type of research –the United States and other developed countries– and the distinctiveness of this novel context.

Keywords: environmental violence, weight gain, health and place, Mexican 'War on Organized Crime'

Introduction

Excess weight has become a major global health concern in the last decades. In 2016 the World Health Organization (WHO) estimated that approximately 39 percent of adults in the world were overweight and 13 percent obese, the latter figure tripling since 1975 (WHO, 2020a). Increases in the availability of cheap processed foods high in sugar and fat, as well as increases in sedentary behaviors are immediate causes of this upward trend (Popkin and Gordon-Larsen, 2004; WHO, 2000). Excess weight is a major risk factor for type 2 diabetes, cardiovascular disease, and other life-shortening diseases (Beaglehole et al., 2011; WHO, 2000). Excess weight also creates economic costs for people, health systems, and societies at large (Beaglehole et al., 2011; Cawley and Meyerhoefer, 2012; WHO, 2000).

Health is shaped by place and living in unsafe environments can be a contributor to excess weight (Lovasi et al., 2009). Specifically, crime-related anxiety can trigger physiological and behavioral responses (e.g., stress eating, fear of going outside), as well as community-wide changes (e.g., built environment decay, socioeconomic deprivation, less access to healthy food options and exercising facilities) that impact dietary intake and activity patterns, leading to weight increases (Lovasi et al., 2009; Yu and Lippert, 2016).

However, the relationship between unsafe or violent environments and weight gain has almost exclusively been examined in developed countries, particularly in the United States (for recent reviews see An et al., 2017; Yu and Lippert, 2016). In the United States, both violence (Sampson, 2012; Sampson and Wilson, 1995) and excess weight (Carroll-Scott et al., 2013; Lovasi et al., 2009) concentrate in socioeconomically deprived and racially segregated communities. As a result, the association between violence and weight has been studied under a relatively narrow set of circumstances, which tend to emphasize concentrated socioeconomic disadvantage and the type of crime and violence that emerge from such circumstances (i.e., 'street crime'). Yet, these environmental conditions are not necessarily representative of how crime or health issues manifest elsewhere in the world. It remains unclear how crime and violence are associated with weight problems in contexts where these factors are not concentrated in disadvantaged neighborhoods and take on different forms.

In contrast to the US context, in many developing countries violence is more widespread and intense, while excess weight can be disproportionately found in middle-class and wealthy households. Latin America offers a great example of these patterns. As explained before, much of the violence in the region is the consequence of organized crime and organized armed groups (e.g., drug trafficking organizations, militias, paramilitary groups), politics, and civic unrest (Auyero, 2007; Villarreal and Yu, 2017). For these reasons, violence is only loosely tied to neighborhood deprivation and much more embedded in institutions and social interactions across social strata and communities. Middle-income and wealthy households are disproportionately more overweight and obese because wealth provides purchasing power to buy excess food and to avoid physically strenuous work, such as blue-collar and agricultural jobs (Kanter and Caballero, 2012; Pampel, Denney, and Krueger, 2012). As a result, wealthier communities typically experience higher rates of overweight or obesity.

In this chapter I study the relationship between violence and weight outcomes in a context where violence and excess weight are not concentrated among the most disadvantaged and both take on forms that impact wealthier communities. In this context I expect: 1) an average positive association between violence and weight gain that is *stronger* than the association found in the United States and other developed countries; and 2) a *more positive* association between violence and high socioeconomic status, young adults, and women. In doing so, I leverage both the theoretical insights constructed in the traditional site of this type of research –the United States and other developed countries– and the distinctiveness of this novel context.

I examine these claims using data from Mexico, a developing country that is one of the most obese (Popkin and Gordon-Larsen, 2004; Caballero, 2007) and deadliest (Muggah and Aguirre Tabón, 2018) in the world. It is estimated that 65 and 29 percent of Mexico's adult population is overweight or obese, respectively, much higher than world averages and the country's percentages in 1975 (37 and 10 percent, respectively) (WHO, 2020b; 2020c). Excess weight is one of the leading causes of disease burden and deaths in the country, accounting for 12.2 percent of all deaths in 2004 (Stevens et al., 2008).

Similarly, violence has consistently been one of the leading causes of disease burden in Mexico (especially for males, Stevens et al., 2008). However, its prominence increased after 2006, when the Mexican government launched the 'War on Organized Crime' (WOC). The WOC has had adverse consequences for several health-related outcomes, such as mental health and depression (Flores Martínez and Atuesta, 2018; Villarreal and Yu, 2017), birth weight (Brown, 2018), and life expectancy/morbidity (Canudas-Romo et al., 2017; Lee and Bruckner, 2017).

I specifically examine the impact of environmental violence –homicides measured at the municipality level– on Mexican adults' (≥18 years-old) Body Mass Index (BMI) and Waist Circumference (WC). Using multi-way fixed effects and a comprehensive set of time-varying individual and household controls that guard against bias from numerous relevant sources, I find a robust positive relationship between homicides at the municipality level and both BMI and WC. The magnitude of the impact is two to three times larger than that uncovered by analyses conducted in developed countries with similar research designs. Supplemental analyses show that these results are robust and lend credibility to the main assumptions built into the research design.

These main findings support the theoretical insights constructed in developed countries (i.e., positive association between violence and weight outcomes), but also reflect the different magnitude and intensity of violence in the region. Sensitivity analyses reveal that the groups for whom the association between violence and weight gain is stronger are those that are already at high risk of being overweight or obese and/or that have been disproportionately involved in –or affected by– the extreme violence of the WOC. For instance, adults with high socioeconomic status (high education/occupational prestige) are more sensitive to violence than those in other socioeconomic groups. I argue that this is the result of more access to food, coupled with the widespread and extreme nature of the violence in this context, which has created anxiety and fear even among middle-class and wealthy sectors of the population (Villarreal, 2015).

Violence also seems to be creating new subgroups of individuals at risk of overweight and obesity. Young adults (18-30 year-olds) are disproportionately affected by violence and are more likely to show symptoms of psychological distress as a consequence (Villarreal and Yu, 2017). This association between violence and weight gain is stronger in this age group than in any other, which is uncommon (Barquera et al., 2009; Barquera et al., 2013; Wang and Beydoun, 2007). Finally, the relationship between violence and weight gain is also stronger for women than for men. Although most of the deadly violence is perpetrated by and against males, Mexico has one of the highest rates of violence against women in the world (UN, 2010) and research has shown that women spend more time worrying about violence than men (Canudas-Romo et al., 2017).

By providing evidence supporting a positive relationship between violence and weight gain, this study contributes to the literature in the United States and other developed countries. Despite strong theoretical grounding, the evidence in favor of this relationship in these countries is weak (An et al., 2017; Yu and Lippert, 2016). Much of the research has failed to detect any impact of violence on excess weight and a recent meta-analysis suggests that this effect is likely to be small (An et al., 2017). It is challenging to disentangle the consequences of violence and socioeconomic deprivation on weight gain in the United States given the high correlation between these three factors. Examining a context where this is not an issue but that nevertheless confirms the general expectation of the theoretical arguments developed in the former context builds upon this theoretical framework, while also substantiating it.

Finally, this study responds to calls in the literature for leveraging better data and measurements of violence and weight gain outcomes. Most prior work has used limited data (e.g., cross-sectional, unrepresentative at either the local or national levels, only children or women) and operationalizations (e.g., subjective measures of crime and weight gain, only one weight-related outcome) (An et al., 2017; Powell-Wiley et al., 2017; Yu and Lippert, 2016). By combining a novel context with large variation in violence (including extreme violence) and a longitudinal approach that is well suited to isolate the influence of such violence, my work advances scholarship at the intersection of the research on communities, violence, and health outcomes.

Excess weight in Mexico

Mexico has become one of the most overweight and obese countries in the world, only behind the United States among the OECD countries. It is estimated that 65 and 29 percent of Mexico's adult population is overweight and obese, respectively, much higher than world averages and the country's percentages in 1975 (37 and 10 percent, respectively) (WHO, 2020b; 2020c). Excess weight is one of the leading causes of disease and deaths in the country, accounting for 12.2 percent of all deaths in 2004 (Stevens et al., 2008). The high death rate attributed to overweight/obesity is partly the result of an underdeveloped health system (Monteverde et al., 2010).

Excess weight is the consequence of 'energy imbalance,' defined as the increase in caloric intake that is not matched by energy expenditure (Kanter and Caballero, 2012). High levels of energy imbalance in Mexico and other developing countries are primarily the result of a 'nutrition transition,' a rapid adoption of a diet and lifestyle characterized by the consumption of highly processed foods, saturated fats, and sugar, as well as lower levels of physical activity (Popkin, 1994; Popkin and Gordon-Larsen, 2004; Rivera et al., 2002).

This ‘nutrition transition’ is helpful to understand the different levels of energy imbalance across socio-demographic groups as well. In Mexico –as in other countries undergoing this transition– females, older individuals, and people with higher socioeconomic status have higher overweight and obesity rates (Barquera et al., 2009; Barquera et al., 2013). Although the reasons behind the gender disparity in overweight and obesity rates are not fully understood, both biological (e.g., estrogen levels and related process such as the menopause) and sociocultural factors (e.g., differences in social norms, attitudes and behaviors towards food consumption and physical activity) are believed to be at play (Kanter and Caballero, 2012; Power and Schulkin, 2008). Similarly, middle-aged people are at higher risk of overweight and obesity due to a combination of biological and sociocultural factors, including natural changes in body composition (Weinheimer, Sands, and Campbell, 2010).

The positive relationship between socioeconomic status and excess weight found in Mexico is also common. Unlike developed countries –where these factors are generally considered to be inversely related (Wang and Beydoun, 2007)– higher socioeconomic status is typically associated with overweight and obesity in developing countries (Dinsa et al., 2012; McLaren, 2007; Sobal and Stunkard, 1989). Wealth provides purchasing power to buy excess food, which is often coupled with less physically strenuous work and, given generally underdeveloped educational systems, preferences and behavioral patterns that have been largely shaped in the absence of scientific information about the benefits of a healthy diet and exercising

(Pampel, Denney, and Krueger, 2012). Contrarily, poor people often have less to eat and are more likely to be employed in hard labor jobs, which constitutes an important source of physical activity (Kanter and Caballero, 2012; Pampel, Denney, and Krueger, 2012).

Environmental violence and weight: Theoretical pathways and previous findings

The consequences of violence and the correlates of weight gains have been intensely studied in Mexico, yet there is no research examining violence as a predictor of weight-related outcomes. Research in other developing countries is scarce. This is an important omission because –unlike the United States and other developed countries–violence is widespread and intense in many of these countries and excess weight can be disproportionately found in middle-class and wealthy households and communities. Given these differences, I argue below that we should expect 1) an average positive impact of violence on weight gain that is larger than the impact found in the United States and other developed countries; and 2) disparities across socioeconomic and demographic groups that reflect the distinctiveness of highly violent developing countries undergoing a 'nutrition transition.'

In the United States and other developed countries violent or unsafe environments can lead to excess weight through several mechanisms. Violence increases fear, anxiety and stress and diminishes mental health (Shinn and Toohey, 2003). The physiological and behavioral responses and adaptations to such stress and anxiety can in turn lead to overweight and obesity. Stress triggers cortisol production, disrupts sleeping and physical activity patterns, and prompts unhealthy eating, all of which are associated with weight gain (Champaneri et al., 2013; Karb et al., 2012; Richardson et al., 2017; Tomiyama, 2019). Moreover, violent or unsafe environments where fear of crime is rampant can discourage outdoor activities or even leaving the house (Foster and Giles-Corti, 2008; Foster et al., 2014). These places might also be characterized by disinvestment, infrastructural decline, socioeconomic disadvantage, limited employment opportunities, and out-migration (Yu and Lippert, 2016; Wilson, 1984). In such contexts the availability and accessibility of healthy foods and the possibility of exercising/walking could be seriously limited, increasing the risk of overweight and obesity (Brown et al., 2019; Foster and Giles-Corti, 2008; Foster et al., 2014; Morland et al., 2002; Morland et al., 2006).

There is evidence that some of these processes are also taking place in the context of the Mexican WOC. Violence has increased fear of crime and affected mental health (Flores Martínez and Atuesta, 2018; Villarreal and Yu, 2017), negatively impacted educational and economic outcomes (Brown and Velásquez, 2017; Caudillo and Torche, 2014; Jarillo et al., 2016), and increased out-migration (Rios Contreras, 2014). These factors could generate individual stress-related processes and behaviors and trigger community-wide changes that could lead to weight gain. Violence has been shown to affect health outcomes closely associated with overweight and obesity, such as birth weight (Brown, 2018), life expectancy (Canudas-Romo et al., 2017), and morbidity due to heart disease (Lee and Bruckner, 2017).

Given the similarity of the social processes underlying the expected relationship between violence and excess weight in both Mexico and the United States/developed countries, I expect a qualitatively similar relationship (positive) in Mexico. However, I also expect this association to be stronger in the Mexican case, an expectation based on the nature and scale of the violence.

Organized violence of the type experienced in Mexico particularly during the WOC is far-reaching in two ways. First, it is not contained in pockets of concentrated disadvantage as in the United States, but rather extends to whole cities and regions. This increases the number of people exposed to violence through either personal victimization or as witnesses to the violence. Both can increase fear of crime and anxiety, prompting stress-related processes and behaviors in more people than in places without this level of violence.

Second, violence related to the WOC is far-reaching because it is more impactful than traditional 'street crime' due to its dramatic nature. People are more likely to remember and be affected by impactful crimes than less serious crimes (Warr, 2000). Seeing and hearing about executions, gun battles, decapitated bodies, and torture has become a common occurrence during the WOC and these events are likely to make people more anxious and fearful of violence (Flores Martínez and Atuesta, 2018; Villarreal and Yu, 2017). The dramatic nature of the WOC is also reflected in its actors. It is common in some regions and cities to see the army and other organized armed groups (e.g., DTOs, militias, paramilitary groups) patrolling the streets and setting up roadblocks, reminding individuals that they are living in a conflict. The impactful nature of the violence would again prompt behavioral responses and generate anxiety even if individuals are objectively unlikely to be personally victimized. I therefore hypothesize that:

Hypothesis 1: Homicides are positively associated with weight gain.

I also argue that the groups that are likely to be more sensitive to this violence are those that are already at high risk of being overweight or obese and/or that have been disproportionately involved in –or affected by– the extreme violence. For these sensitive groups, violence can greatly heighten anxiety, disrupt sleeping patterns, increase stress eating, and discourage healthy habits such as walking and exercising, all of which are associated with weight gain (Tomiyama, 2019).

I argue specifically that women, young adults, and people with high socioeconomic status are more sensitive to violence. Women are typically underrepresented in violent events as both victims and perpetrators, but they often report higher levels of fear of crime and distress than men, a result that has been attributed to their perception of vulnerability (Jackson, 2009). Similarly, most of the deadly violence in Mexico before and during the WOC has been perpetrated by and against males. However, women are less safe in Mexico than in other places, as the country has had one of the highest rates of violence against women in the world (especially sexual violence, United Nations, 2010), punctuated by extreme and highly publicized femicides (UN, 2017). Women might be especially vulnerable in contexts such as this one where violence against women is prevalent and salient. During the WOC women have spent more time worrying about violence taking place both outside and inside their household than men (Canudas-Romo et al., 2017). This suggests that women should be more sensitive to violence and the fear and stress that it generates. This expectation is stated in the following hypothesis:

Hypothesis 2: The association between homicides and weight gain is more positive for women than for men.

Older adults are typically more fearful than younger adults, despite the fact that they are also underrepresented in violent events. Again, vulnerability is often cited as a reason for this seemingly paradoxical finding. But in the context of the WOC younger adults exhibit higher psychological distress as a result of violence, perhaps reflecting their objectively higher exposure to violence and risk of victimization (Villarreal and Yu, 2017). Then I hypothesize that:

Hypothesis 3: The association between homicides and weight gain is more positive for young adults than for older adults.

Adults with high socioeconomic status should also be more sensitive to violence. People living in middle-class and wealthy communities are likely to experience, witness, and hear about violence given its extra-local and extreme nature in Mexico, especially during the WOC (Villarreal, 2015). In fact, some DTOs have specifically targeted middle-class and wealthy communities and households to expand their revenue sources. Crimes such as extortions and kidnappings have increased substantially along with homicides in some of the regions that have suffered the most due to the WOC and have impacted middle-class and wealthy people disproportionately (Shirk and Wallman, 2015). Cattle-ranchers, agricultural producers, restaurateurs, and many other business owners have been extorted, kidnapped, murdered or forced to shut down (Deraga, 2014; Ornelas, 2013; Villarreal, 2015). Middle-class and wealthy communities had not been exposed to this level and type of violence before, plausibly making them more sensitive to it. The fear and anxiety generated by this violence can intensify the already high risk of overweight and obesity resulting from food surpluses and sedentary behaviors among adults with high socioeconomic status. Therefore, I hypothesize that:

> **Hypothesis 4:** The association between homicides and weight gain is more positive for adults with high socioeconomic status than for those with low socioeconomic status.

A handful of studies have examined weight gain in a developing country with high homicide and violence rates that could arguably resemble Mexico. Set in Belo Horizonte, Brazil, and Cali, Colombia they provide mixed evidence of a link between homicides and weight gain. Two of them found a positive and statistically significant relationship (Martínez, Prada and Estrada, 2018; Mendes et al., 2013) but the other could not detect an association (Velásquez-Meléndez, Mendes and Padez, 2013). These are single-city studies that did not follow individuals across time and place and did not examine heterogeneity across several subpopulations. As such, they are valuable to describe the association between violence and weight, but their implications for the analysis of the impact of violence on weight across time and space for developing countries with high levels of violence are unclear.

These studies conducted in developing countries share many of the limitations that have hampered research in the United States and other developed countries. A key shortcoming is that most analyses rely on cross-sectional data (Yu and Lippert, 2016). Cross-sectional analyses could be detecting a spurious effect of violence due to selection. For example, if overweight or obese people were more likely to live in violent environments or healthier individuals were more likely to flee from them, the analyses would likely pick up an ‘effect’ that might not exist in reality.

Analyses that have employed longitudinal data and individual fixed-effects to account for these influences could not detect an association between safety/crime/violence and weight outcomes (e.g., Datar, Nicosia, and Shier, 2013; McTigue at al., 2015; Powell-Wiley et al., 2017). This suggests that the association that cross-sectional studies are picking up might be upwardly biased due to the lack of sufficient controls for environmental and individual factors that are correlated with both violence and weight outcomes.

The samples in many prior studies are limited in other ways. Some are not representative (either locally or nationally) and probably lack enough violence heterogeneity to detect smaller effects, as the interviewees come from geographically and socioeconomically homogenous environments (An et al., 2017). Some only include segments of a population (e.g., children, women, African American or an interaction of these groups) (An et al., 2017; Yu and Lippert, 2016), making generalizations beyond these segments questionable. Additionally, many studies do not use objective measures of weight gain and/or violence. This is an important limitation because objective measures of weight gain can reduce measurement error. Objective measures of violence are also important because they can more comprehensively help us understand how violence impacts individuals, as many of the pathways through which this effect might take place are not related to individual perceptions (Sharkey, 2018).

Finally, the majority of studies examined only one weight-related outcome, primarily BMI, another important constraint because other indicators of weight might be better predictors of morbidity and risk of serious and/or chronic illnesses. For instance, waist circumference (WC) appears to be a better predictor of type 2 diabetes (Wang et al., 2005) and cardiovascular disease (Bastien et al., 2014) than BMI. The reason for this is that whereas BMI is a measure of overall weight and is not well suited to identify cases in which elevated body mass is the consequence of built muscle or lean mass instead of fat, WC specifically measures fat concentration in the abdomen, a critical region (Bastien et al., 2014; López-Alvarenga et al., 2003).

Hence, despite strong theoretical grounding, there is limited evidence supporting a positive relationship between violence and weight gain in the United States and other developed countries or elsewhere. Much of this research has failed to detect any impact of violence on excess weight and a recent meta-analysis suggests that this effect is likely to be small, if it exists at all (An et al., 2017). The evidence in favor of a positive association mostly comes from cross-sectional studies with measurement shortcomings. Longitudinal studies have been for the most part conducted with children and adolescents and also have measurement limitations.

My study responds to calls in the literature for leveraging better data and measurements of violence and weight gain outcomes. I leverage a nationally representative sample of adults, objective measures of violence and two weight-related outcomes and, most importantly, longitudinal data and a research design that robustly accounts for unobserved individual and environmental characteristics that could be related to both violence and weight outcomes. This helps allay concerns about bias stemming from the two most common sources in a study of an environmental predictor and an individual outcome.

Data and measures

I combine two sources of data to examine the relationship between environmental violence and weight-related outcomes, operationalized as BMI and WC. I use objective measures of height, weight, and waist circumference from the Mexican Family Life Survey (MxFLS). Trained surveyors measured adults' (≥18 years-old) height, weight, and waist circumference and took their socio-demographic information, recovering 49,993 and 49,515 observations for BMI and WC, respectively. Due to its structure (panel) and rich set of variables –including objectively measured height, weight, and waist circumference– this data set has been widely used to examine weight-related issues (e.g., Brown, 2018; Creighton et al., 2011) and the consequences of crime and violence (e.g., Brown and Velásquez, 2017; Villarreal and Yu, 2017).

The outcome of interest is excess weight, which has been traditionally measured using the body mass index (BMI), operationalized as the ratio of weight (kilograms) to height (meters) squared (Kg/m^2). The World Health Organization (WHO) has established cutoff values to define overweight (BMI≥25) and obese (BMI≥30) adults (WHO, 2020a). However, these standard cutoff points do not always track the actual risk of morbidity and serious illness related to obesity. Research has shown that this risk varies across populations, which is why different cutoff points have been suggested. For instance, for Asians and Mexicans, as well as for short stature individuals (typically women≤1.50 mts. and men≤1.60 mts.) lower thresholds have been recommended (overweight BMI≥23; obesity BMI≥25) (Hubbard, 2000; Lara-Esqueda et al., 2004; López-Alvarenga et al., 2003; Monteverde et al., 2010). Additionally, as explained before, exclusively using BMI as the outcome might generate misleading results because other measures of excess weight might be better predictors of morbidity and disease risk.

To offset these issues with BMI and its cutoff points, I follow recent recommendations and use both BMI and WC as indices of weight (Bastien et al., 2014; Powell-Wiley et al., 2017). Similar patterns of results across these two measures would boost the confidence in the findings. Consistent with standard definitions, I measure BMI as Kg/m^2 and WC in centimeters. I also use the continuous measures of these two variables as outcomes in recognition of the somewhat arbitrary nature of cutoff points (Hubbard, 2000; Caballero, 2007) and the fact that using cutoff values throws away important information and reduces variation, leading to reduced statistical power and increased measurement error (Lovasi et al., 2012).

The main predictor is the municipality homicide count in the months prior to the outcome, which I take from INEGI. As explained before, these data are generally used in similar studies because homicide is the most extreme violent crime and the most reliably measured in Mexico and abroad (Mosher, Miethe and Hart, 2011; Shirk and Wallman, 2015). Additionally, homicides capture the existence and intensity of the WOC because most of the violence after 2007 was due to the armed conflict and its gruesomeness was highly correlated with homicide levels, meaning that homicide counts are the best proxies available for both the quantity and nature of deadly violence in Mexico (Shirk and Wallman, 2015).

I also introduce socioeconomic and demographic individual and household controls. At the individual level I include age, marital status, education, employment, and health insurance coverage. At the household level I include the number of children in the household (less than 15 years old) and a set of variables that indicate if the household has more than two people per room, at least one adult earning more than 2 minimum wages per day, at least one adult with a middle-school education or higher, and at least one member currently living in the United States. I also include binary variables for household shocks (deaths, hospitalizations, unemployment or business failure, loss of home or business due to a natural disaster, and crop and livestock loss), receipt of governmental subsidies, female-headed household, and victimization, the latter operationalized as personal (kidnapping, harassment/sexual abuse, robbery/assault, and bodily injury) or household (breaking and entering home, business or plot/land) victimization in the previous two years.

I exclude 3.4 (BMI) and 1.7 (WC) percent of observations for pregnant or lactating women, as commonly done in the literature (e.g., Perez Ferrer et al., 2014). As expected, BMI and WC are highly correlated in the resulting sample (0.79, $p < 0.001$). I additionally exclude observations with missing data on the predictors and control variables (in those models that include controls), which represent less than 3 percent of the sample. Approximately 21 percent of observations do not vary within individual or municipality and are thus dropped from the analyses, as my research design requires this variation (see below). More than half of these observations correspond to individuals added to the sample in the last wave. Only about 16 percent of the individuals interviewed in the first wave who provided socioeconomic information were not interviewed again. Approximately 60 percent were interviewed in all three waves. These attrition rates are comparable to those of prior work using panel data in this literature (see An et al., 2017). Depending on the specific analysis, the sample size varies between 36,957 and 38,423 individual-wave observations. Summary statistics are reported in the Appendix.

Table 2.1 Descriptive Statistics

	Body Mass Index		Waist Circumference	
Variable	Mean or %	SD	Mean or %	SD
Outcomes				
Body Mass Index	27.79	5.31		
Waist Circumference			90.76	13.34
Predictors				
Homicides *t* - 1 year	35.73	72.70	36.13	73.42
Homicides *t* - 2 years	65.74	128.97	66.43	130.29
Individual controls				
Age	43.35	16.16	43.32	16.12
Marital status (married, cohabitating)	71.80%		71.78%	
Education (none or pre-k)	11.66%		11.67%	
Education (elementary school)	43.76%		43.71%	
Education (middle school)	23.86%		23.86%	
Education (high school)	10.78%		10.82%	
Education (college or graduate)	9.95%		9.95%	
Employment	58.74%		58.95%	
Health insurance	51.77%		51.83%	
Household controls				
Female headed	18.60%		18.51%	
Adults middle school	47.67%		47.77%	
Adults minimum wage	44.90%		44.92%	
Children	1.362	1.418	1.362	1.419
US migration	37.26%		37.32%	
Government subsidies	15.10%		15.33%	

Table 2.1 (Continued)

Crime victimization	0.044	0.150	0.044	0.150
Shocks	27.08%		27.17%	
Municipality population (log)	11.46	1.708	11.45	1.715
Variables used in fixed-effects				
Wave 1	32.32%		32.02%	
Wave 2	35.56%		34.95%	
Wave 3	32.11%		33.03%	
Year				
2002	32.32%		32.02%	
2005	24.28%		23.84%	
2006	11.28%		11.11%	
2009	19.88%		20.81%	
2010	9.40%		9.41%	
2011	2.59%		2.57%	
2012	0.17%		0.17%	
2013	0.08%		0.07%	
Month				
January	4.68%		4.63%	
February	2.46%		2.39%	
March	2.60%		2.60%	
April	11.89%		11.83%	
May	19.89%		19.72%	
June	18.03%		17.82%	
July	8.66%		8.49%	
August	9.03%		9.13%	
September	6.13%		6.40%	
October	6.20%		6.51%	
November	6.19%		6.28%	
December	4.24%		4.20%	
Community size				
0-2,499	44.14%		44.08%	
2,500-14,999	11.58%		11.54%	

Table 2.1 (Continued)

15,000-99,999	9.65%	9.64%
100,000 or more	34.64%	34.74%
Individuals	14946	15029
Municipalities	139	139
N	36957	37341

ABBREVIATION: SD = standard deviation.

Estimation strategy

The goal of this chapter is to examine the impact of environmental violence on weight by accounting for environmental and individual confounders. I capitalize on two features of the data to do so. First, the panel nature of the data allows me to use repeated observations of individuals to control for unobserved and fixed characteristics that could be connected to both the predictor and the outcome at the individual level. Second, I exploit the relative timing of BMI and WC measures with respect to homicidal events in the same environment (Sharkey, 2010). People were measured in the same municipality and wave across different months, allowing me to control for unobserved and fixed environmental level factors related to these outcomes and violence. Formally, I estimate linear regression models with the following structure:

$$y_{ijwtm} = \beta_0 + \beta_1 Hom_{jt} + \beta_2 \boldsymbol{IC}_{iw} + \beta_3 \boldsymbol{HC}_w + \beta_4 \boldsymbol{MC}_{jw} + \alpha_t + \alpha_m + \alpha_{jw} + \alpha_i + \mu_{ijwtm} \quad (1)$$

where y_{ijwtm} is defined as the weight-related outcome of interest (BMI or WC) for individual i, located in municipality j, in wave w, year t, and month m; Hom_{jt} is the homicidal count in municipality j in the t year(s) prior to the outcome; $\boldsymbol{IC}_{iw}$, $\boldsymbol{HC}_{w}$, and $\boldsymbol{MC}_{jw}$ are vectors of individual, household and municipality/community characteristics in wave w, respectively; α_{jw} is the municipality-by-wave fixed-effects and α_i the individual fixed-effects; α_t and α_m are calendar year and month fixed-effects, respectively, and μ_{ijwtm} is the idiosyncratic error term. I use clustered errors at the municipality level to account for the loss of independent variation in the error term. Homicide counts are aggregated one and two years prior to the outcome in different specifications to examine if the results are sensitive to the duration and persistence of violence.

I use homicide counts instead of rates because rates can be extremely sensitive to small changes in homicides when the population size is also small, in which case rates can be deceptive (Slocum et al., 2013). This is likely to be the case in this application because a substantial minority of observations in my analytical samples comes from approximately 20 percent of municipalities that in 2002 had a population of 15,000 people or less. However, I introduce the natural log of the municipality population and the community size (≤2,500; >2500 and ≤15,000; >15,000 and ≤100,000; >100,000) as separate controls ($\boldsymbol{MC}_{jw}$) to account for the impact of the number of potential victims and offenders on weight (see Chamlin and Cochran, 2004).

My estimate of β_1 can be interpreted as the linear change in the outcome related to a one-homicide increase in the municipality of residence in the prior year(s). In retrieving this estimate these models account for seasonal fluctuations and year-to-year changes while also eliminating bias stemming from unobserved factors that remain constant over individuals and over municipalities at each wave.

This approach helps allay concerns about biased estimates because it eliminates systematic variation stemming from unobserved and time-invariant individual and environmental characteristics, two sources of bias that have traditionally dogged research on environmental influences on excess weight and other individual characteristics. For instance, individual fixed-effects control for constant genetic influences on physical complexion and weight, entrenched tastes and habits related to exercising and dieting, and cultural predispositions and expectations that have a fixed relationship with these outcomes and that could also influence homicides levels. In turn, municipality-by-wave fixed-effects control for demographic and structural factors of the larger residential environment, assuming that they remain constant within each wave. These include poverty and inequality, the amount and quality of schools, and 'obesogenic' characteristics such as the availability of unhealthy eating options and the lack or deficiencies of exercising and recreational resources and infrastructure. Municipality-by-wave fixed effects also account for governmental policies that could be connected to both violence and excess weight through multiple pathways. For example, cash transfer and supplemental nutrition assistance programs could increase healthy food consumption and alleviate socioeconomic disadvantage, which in turn could also reduce crime and violence.

A small percentage of the analytical sample (~1 percent) moved to a different municipality between waves. This migration could be the consequence of homicide increases in the municipality of origin prior to the move, which could bias the results if those fleeing are systematically different from those staying in a violent environment in ways that also impact weight outcomes. However, the extreme violence of the WOC was sudden and homicide levels were either stable or declining in most municipalities prior to the WOC (Brown, 2018). This makes it unlikely that individuals were responding to violence when migrating out of municipalities. Ancillary analyses in the Appendix confirm this conclusion. These are linear probability models with municipality migration as the outcome and homicide counts in the municipality of residence as predictors. The multi-way fixed effects of Equation (1) are also retained. The models provide no evidence that migration is systematically related to violence, on average. Nevertheless, to circumvent any potential bias arising from endogenous migration of specific subgroups, I assign those who changed municipalities to their prior municipality instead of their current one, eliminating municipality choices made after the escalation of violence began (Brown, 2018). This decision is also justifiable because it is not possible to pin down the timing of the migration, which would otherwise open the possibility of the individual not being exposed to the violence of the municipality where s/he currently lives, but rather to that of the municipality where s/he used to live.

Results

Main analyses

I present the results of the main analyses in Tables 2.2 and 2.3. Homicides are aggregated over one and two years prior to the measurement of the outcome variables and each term is then

Table 2.2 Fixed-Effects Models of Body Mass Index with Homicides as Predictor

Homicides	Body Mass Index			
	(1)	(2)	(3)	(4)
t - 1 year	0.0032***	0.0032***		
	(0.0009)	(0.001)		
t - 2 years			0.0023***	0.0023***
			(0.0006)	(0.0007)
Controls	No	Yes	No	Yes
R^2	0.88	0.89	0.88	0.89
N	38,024	36,957	38,024	36,957

NOTE: Results presented are coefficients with standard errors clustered at the municipal level in parentheses. All the models include individual, municipality-by-wave, calendar year and month, and community type fixed-effects. Models with additional controls also include the individual and household variables in Table 2.1, as well as the natural log of the municipality population.
*** p<0.01, **p<0.05, *p<0.10 (two-tailed tests)

introduced in separate models with and without individual- and household-level controls. Models with controls adjust for potential confounding stemming from these variables that would bias the estimates, while models without controls exclude the possibility that these variables could be blocking a potential pathway between homicide and the outcomes, which would generate a spurious relationship between them (Elwert and Winship, 2014). The models show a consistent pattern of increased BMI and WC as homicides increase, supporting the positive association presented in Hypothesis 1. In the case of BMI, homicides remain significant at the $p<0.05$ level across all the specifications. A one-homicide increase in the previous year increases BMI by approximately 0.003 points (Kg/m^2), on average, while the same increase of homicides in the previous 2-year period is related to an average increase of 0.002 BMI points. For WC estimates hover around 0.003 centimeters.

Table 2.3 Fixed-Effects Models of Waist Circumference with Homicides as Predictor

Homicides	Waist Circumference			
	(1)	(2)	(3)	(4)
t - 1 year	0.0034*	0.0038**		
	(0.002)	(0.002)		
t - 2 years			0.0030**	0.0033**
			(0.001)	(0.001)
Controls	No	Yes	No	Yes
R^2	0.86	0.86	0.86	0.86
N	38,423	37,341	38,423	37,341

NOTE: Results presented are coefficients with standard errors clustered at the municipal level in parentheses. All the models include individual, municipality-by-wave, calendar year and month, and community type fixed-effects. Models with additional controls also include the individual and household variables in Table 2.1, as well as the natural log of the municipality population.
*** p<0.01, **p<0.05, *p<0.10 (two-tailed tests)

To aid in the interpretation of these results, I use residualized variances to determine the changes in the outcomes as a result of plausible changes in homicides.[6] Table 2.4 shows that a 1 SD change in homicides increases BMI by approximately 0.024 points (Kg/m^2), while a 3 SD change increases BMI by about 0.07 points. These changes in homicides would make approximately 0.26 and 0.59 percent of the sample more overweight (BMI≥25) or 0.11 and 0.41

[6] Employing residualized variances –instead of overall variances– is key in assessing the substantive significance of these effects because the multiple fixed-effects introduced in the specifications considerably limit the variation available for the analyses. In this scenario using overall variances can be misleading (Mummolo and Peterson, 2018).

percent more obese (BMI≥30), respectively. Similarly, a 1 SD change in homicides measured two years prior increases WC by 0.013 points and a 3 SD change by 0.038. These changes would make 0.87 percent of the males in the sample and 1.09 percent of the females more obese.

Table 2.4 Effects of Homicides on Weight-related Outcomes Based on Homicides' Residualized Variances

Homicides	Body Mass Index			Waist Circumference		
	1 SD	2 SD	3 SD	1 SD	2 SD	3 SD
t - 1 year	0.0235	0.0470	0.0704	0.0103	0.0206	0.0308
t - 2 years	0.0238	0.0475	0.0713	0.0128	0.0255	0.0383

NOTE: Results presented are based on the results in Columns (2) and (4) of Tables 2.2 and 2.3.
ABBREVIATION: SD = standard deviation.

Table 2.5 Standardized coefficients of Homicides on Weight-related Outcomes

Homicides	Standardized coefficients	
	Body Mass Index	Waist Circumference
t - 1 year	0.044***	0.021**
t - 2 years	0.055***	0.032**

NOTE: Results presented are based on the results in Columns (2) and (4) of Tables 2.2 and 2.3.
ABBREVIATION: SD = standard deviation.

These are modest changes but considerably larger than those found in comparable studies. For instance, a meta-analysis of longitudinal studies examining the relationship between unsafe neighborhoods and BMI in children and adolescents found an impact of 0.018 standard deviations (An et al., 2017). As I show in Table 2.5, the standardized coefficients computed using the estimates with individual- and household-level controls in Tables 2.2 and 2.3 are two to three times larger. Moreover, none of the studies reviewed used multi-way fixed effects to adjust for unobserved and constant individual factors *and* environmental trends, which means that their estimates might be biased upwards if violence is positively correlated at the community level with unobserved factors that could also increase weight. This suggests that the true gap between my estimates and those of prior research might be larger. In fact, the only longitudinal study carried out with a sample of adults and with both BMI and WC as outcomes could not detect a relationship between them and police-recorded crime (Powell-Wiley et al., 2017).

Sensitivity to environmental violence

I have argued that violence should have a heterogeneous impact on weight across gender, age, and socioeconomic status in a way that reflects the Mexican context as a developing country undergoing a 'nutrition transition' that has experienced extreme levels of violence. In this section I test if subgroups formed by these factors are more sensitive than others to violence. To do so, I add interaction terms with homicides to the specifications in the main analyses. To allow for potential nonlinearity, I use categorical variables for age (≤30, >30 and ≤45, >45 and ≤60, >60), education [none or low (no education, preschool, elementary school), medium (middle school), high (high school, college, graduate school)], and occupational prestige (pink-collar jobs,[7] blue-collar jobs, white-collar jobs).[8] I introduce each of these interaction terms and the interaction

[7] Pink-collar jobs are defined as those occupations in the service sector that have been traditionally associated with women, such as school teachers, caregivers, and nurses (Howe, 1977).

[8] Occupational prestige also includes the categories of unemployed, student, house-maker, retiree, and agricultural worker, but these categories are omitted from the table to conserve space.

term for gender in separate models. In addition to individual tests of significance I include F-tests for the null hypothesis that the overall effect (interaction plus lower-order terms) equals zero. Results without controls are omitted to conserve space but are substantially the same.

Table 2.6 Fixed-Effects Models of Weight-related Outcomes with Homicides as Predictor Interacted with Gender

Homicides	Body Mass Index		Waist Circumference	
	(1)	(2)	(3)	(4)
t - 1 year	0.0021**		0.0008	
	(0.001)		(0.002)	
t - 1 year *X* female	0.0017**		0.0045***	
	(0.0006)		(0.001)	
t - 2 years		0.0014**		0.0013
		(0.0006)		(0.001)
t - 2 years *X* female		0.0013***		0.0032***
		(0.0004)		(0.0009)
F-test	0.002	0.0007	0.0004	0.0003
R^2	0.89	0.89	0.86	0.86
N	36,951	36,951	37,335	37,335

NOTE: Results presented are coefficients with standard errors clustered at the municipal level in parentheses. All the models include individual, municipality-by-wave, calendar year and month, and community type fixed-effects and control for the individual and household controls in Table 2.1, as well as the natural log of the municipality population.
*** p<0.01, **p<0.05, *p<0.10 (two-tailed tests).

The results are presented in Tables 2.6, 2.7, 2.8, and 2.9. They show that all of these factors shape how homicides impact weight gains in ways that reinforce the risk of overweight and obesity for some groups already at high risk (women and adults with high socioeconomic status) and increase the risk for other groups at lower risk (young adults). In support of Hypothesis 2, female adults are more sensitive to increases in homicides than men, as indicated by the positive and significant coefficients on the interaction terms between homicides and female and the corresponding F-tests (Table 2.6).

Table 2.7 Fixed-Effects Models of Weight-related Outcomes with Homicides as Predictor Interacted with Age

Homicides	Body Mass Index		Waist Circumference	
	(1)	(2)	(3)	(4)
t - 1 year	0.006***		0.008***	
	(0.001)		(0.002)	
Age (18-30)				
31-45	0.755***		1.673***	
	(0.101)		(0.263)	
46-60	0.638***		1.578***	
	(0.146)		(0.406)	
>60	0.012		0.467	
	(0.213)		(0.561)	
t - 1 year *X* age (18-30)				
31-45	-0.003***		-0.0051***	
	(0.001)		(0.002)	
46-60	-0.005***		-0.0054***	
	(0.001)		(0.002)	
>60	-0.007***		-0.009***	
	(0.001)		(0.002)	

Table 2.7 (Continued)

t - 2 years		0.0038***		0.0058***
		(0.0007)		(0.001)
Age (18-30)				
31-45		0.767***		1.725***
		(0.101)		(0.263)
46-60		0.661***		1.641***
		(0.147)		(0.409)
>60		0.035		0.549
		(0.215)		(0.566)
t - 2 years *X* age (18-30)				
31-45		-0.0017***		-0.0035***
		(0.0005)		(0.0009)
46-60		-0.0032***		-0.0038***
		(0.0006)		(0.001)
>60		-0.0043***		-0.0062***
		(0.0007)		(0.001)
F-test	0.0000	0.0000	0.0000	0.0000
R^2	0.89	0.89	0.86	0.86
N	36,957	36,957	37,341	37,341

NOTE: Results presented are coefficients with standard errors clustered at the municipal level in parentheses. All the models include individual, municipality-by-wave, calendar year and month, and community type fixed-effects and control for the individual and household controls in Table 2.1, as well as the natural log of the municipality population. *** p<0.01, **p<0.05, *p<0.10 (two-tailed tests).

Young adults (18 to 30-year-olds) are also more sensitive to homicides (Table 2.7), which supports Hypothesis 3 and suggests that violence could be increasing the risk of overweight and obesity for a group that typically has lower risk than older adults. Specifically, the negative and statistically significant interaction terms for all older age groups suggest that the impact of violence in these older individuals is less than in younger adults. The results show a clear pattern of diminishing impact as age increases. This might be driven by the objective risk of victimization and the psychological distress that young adults are facing in the extremely violent context of the WOC.

Table 2.8 Fixed-Effects Models of Weight-related Outcomes with Homicides as Predictor Interacted with Education

Homicides	Body Mass Index		Waist Circumference	
	(1)	(2)	(3)	(4)
t - 1 year	0.0004		0.0007	
	(0.001)		(0.002)	
Education				
Low				
Medium	0.061		0.473	
	(0.180)		(0.584)	
High	0.522*		1.454*	
	(0.271)		(0.862)	
t - 1 year *X* education				
Medium	0.0037***		0.0019	
	(0.0009)		(0.002)	
High	0.004***		0.005***	
	(0.0007)		(0.002)	
t - 2 years		0.0003		0.001
		(0.0008)		(0.002)

Table 2.8 (Continued)

Education				
Low				
Medium		0.046		0.462
		(0.182)		(0.589)
High		0.503*		1.413
		(0.270)		(0.862)
t - 2 years *X* education				
Medium		0.0023***		0.001
		(0.0006)		(0.001)
High		0.0024***		0.0033***
		(0.0005)		(0.001)
F-test	0.0000	0.0000	0.0005	0.0012
R^2	0.89	0.89	0.86	0.86
N	36,957	36,957	37,341	37,341

NOTE: Results presented are coefficients with standard errors clustered at the municipal level in parentheses. All the models include individual, municipality-by-wave, calendar year and month, and community type fixed-effects and control for the individual and household controls in Table 2.1, as well as the natural log of the municipality population.
*** p<0.01, **p<0.05, *p<0.10 (two-tailed tests).

Finally, the results in Tables 2.8 and 2.9 also support Hypothesis 4, which describes the expectation that adults with higher socioeconomic status should be more sensitive to violence. Table 2.8 shows that violence has a larger positive impact on both weight outcomes in those adults with the higher educational attainment compared to those with low education. Similarly, Table 2.9 shows that the positive impact of violence is larger among those in a white-collar occupation, who typically enjoy a higher occupational status and income than pink-collar workers. People with high socioeconomic status are more likely to be overweight or obese and the nature of the violence during the WOC can increase this likelihood.

Table 2.9 Fixed-Effects Models of Weight-related Outcomes with Homicides as Predictor Interacted with Occupational Prestige

Homicides	Body Mass Index		Waist Circumference	
	(1)	(2)	(3)	(4)
t - 12 months	0.002*		0.002	
	(0.001)		(0.002)	
Occupation				
Pink-collar				
Blue-collar	-0.034		-0.158	
	(0.117)		(0.312)	
White-collar	0.156		0.029	
	(0.130)		(0.341)	
t - 12 months *X* occupation				
Blue-collar	0.0003		-0.0014	
	(0.001)		(0.002)	
White-collar	0.0022**		0.005**	
	(0.0009)		(0.002)	
t - 24 months		0.002**		0.002
		(0.001)		(0.0015)
Occupation				
Pink-collar				
Blue-collar		-0.028		-0.120
		(0.120)		(0.315)

Table 2.9 (Continued)

White-collar		0.157		0.020
		(0.134)		(0.346)
t - 24 months				
X occupation				
Blue-collar		0.0001		-0.0012
		(0.001)		(0.001)
White-collar		0.0012*		0.003**
		(0.0006)		(0.001)
F-test	0.000	0.000	0.000	0.000
R^2	0.89	0.89	0.86	0.86
N	34,717	34,717	35,087	35,087

NOTE: Results presented are coefficients with standard errors clustered at the municipal level in parentheses. All the models include individual, municipality-by-wave, calendar year and month, and community type fixed-effects and control for the individual and household controls in Table 2.1, as well as the natural log of the municipality population. Occupational prestige also includes the categories of unemployed, student, housemaker, retiree, and agricultural worker but are omitted to conserve space.
*** p<0.01, **p<0.05, *p<0.10 (two-tailed tests).

Robustness checks

The results are robust to numerous alternative model specifications and identification threats. A key assumption of the main models is that the causal ordering is correct. This entails that the homicide levels after the measurement of the outcomes should not affect the scores. I conduct placebo tests using similar models but with homicides measured after the weight-related measurements to assess this possibility. The analyses in the Appendix show that none of the coefficients are close to statistical significance.

A second threat to the validity of the results is selective attrition. Although attrition rates for the MxFLS were moderate in general and within the ranges seen in longitudinal studies, it is important to assess if this attrition is related to violence. If so, attrition can generate selection bias. To exclude this possibility, I perform linear probability models similar to those used to examine municipality migration in which I define the outcome as a dichotomous variable for whether there is the necessary survey responses for the main analyses for any given individual in each wave or not, starting from the first wave in which they were interviewed. The results reported in the Appendix suggest that homicide levels do not predict attrition. One of the coefficients is marginally significant, but in the opposite direction.

I also introduce indicator variables for soft drink consumption in the house or at parties and alcohol consumption at parties, as well as continuous variables for the average amount of time spent exercising per day (in minutes) and the total amount of screen time (television plus internet) in the prior week (in hours). The reasoning for their inclusion is that caloric intake and physical activity are often considered the main immediate precursors of overweight and obesity. Homicides could be capturing the impact of these variables on weight, which would make the homicide coefficients upwardly biased. However, this possibility is not born out in the analysis (Appendix). The added variables are related to BMI and WC in the expected direction (positive for soft drinks, alcohol, and screen time and negative for exercise) and in most cases the coefficients are large and statistical significant, but the coefficients on the homicide terms are almost unchanged.

In the Appendix I also reproduce the main analyses excluding observations with BMI≤18.5, considered to be the underweight threshold. Underweight individuals are at increased risk of mortality, which implies that for this subpopulation gaining weight could potentially be beneficial (Aune et al., 2016). The findings are consistent with the main results, indicating that weight gains as a result of homicides are not driven by the impact of homicides on this subpopulation. This supports the conclusion that violence is an environmental factor that could plausibly diminish the health of individuals through its effect on increased weight. I also include the women who were pregnant or lactating at the time the measurements were taken and I add an indicator variable for these conditions. As expected, the results in the Appendix show that pregnancy/lactation is positively related to weight, but the results regarding homicides remain substantially the same.

Discussion

A growing body of work has analyzed the relationship between crime and violence and excess weight, building on insights from research on 'neighborhood effects,' criminology, and non-communicable diseases. This work has found tentative evidence supporting a positive association between living in unsafe environments and weight gain. Yet this research has overwhelmingly been conducted in developed countries, mostly the United States. This context offers a relatively narrow set of circumstances, which tend to emphasize concentrated socioeconomic disadvantage and the type of crime and violence that emerge from such circumstances (i.e., 'street crime'). It remains unclear how crime and violence are associated with weight problems in contexts where violence and weight issues are not concentrated in disadvantaged neighborhoods and take on different forms.

In this chapter I study violence and weight gain in Mexico. In contrast to the United States context, violence in Mexico is more widespread, intense, and dramatic (partly as a consequence of the WOC), while excess weight can be disproportionately found in middle-class and wealthy households (as a result of the country's ongoing 'nutrition transition'). Based on the theoretical insights from prior work in the United States and other developed countries and the characteristics of this novel context, I expect: 1) an average positive association between violence and weight gain that is *stronger* than the association found in the United States and other developed countries; and 2) a *more positive* association between violence and high socioeconomic status, young adults, and women. I test these claims by examining the impact of municipality homicides on Mexican adults' (≥18 years-old) Body Mass Index (BMI) and Waist Circumference (WC). In support of the first claim, my findings indicate a robust positive impact that is two to three times larger than that uncovered by analyses conducted in developed countries with similar research designs. In support of my second claim, I find that women, young adults, and people with high socioeconomic status are more sensitive to violence.

These findings build on prior work conducted in developed countries. Substantively, the evidence in favor of the theorized positive relationship between violence and weight gain has been mixed (see An et al., 2017; Yu and Lippert, 2016). Indeed, much of this research has failed to detect any impact of violence on excess weight. Methodologically, the data and measurements brought to bear on this question have often been limited in important ways. I find strong evidence in favor of the theorized relationship while also improving on many of the methodological and data limitations of previous work.

But beyond improvements in research design, data, and measurements, my work builds upon prior work by leveraging both the theoretical insights constructed in the United States, on the one hand, and the distinctiveness of a context where violence and excess weight are not concentrated among the most disadvantaged and both take on forms that impact wealthier communities, on the other. My research shows that the positive relationship between violence and excess weight hypothesized in developed countries could be the result of general mechanisms at work in many settings. But I also show that a different context influences the magnitude of the relationship and determines the different groups that are more sensitive to violence.

Future research should address some of the issues raised by this work that could not be fully addressed here due to data limitations. First, it is important to operationalize environmental violence at smaller levels of aggregation, such as neighborhoods or blocks, to compare it with the results provided in this chapter and the literature. Second, testing different types of environmental violence would also be a promising extension of this work. This could entail distinguishing among different types of homicide (e.g., homicides as a result of domestic violence vs. organized crime) or using different crimes (e.g., robbery, kidnapping). Finally, research can also test these claims in other developing countries with extreme violence to corroborate the findings presented in this chapter.

Social scientists have recognized the importance of residential environments for the health of individuals and have identified violence as a predictor of weight gain, one of the most pressing health issues of our time. However, most of what we know about this relationship comes from research conducted on a limited range of environments. As my work shows, expanding this range can lead to a more general theoretical and empirical understanding of these phenomena.

3

Fear of crime, armed conflict, and collective efficacy in Mexico

Abstract

Research has seldom examined how fear of crime is influenced by armed conflicts using a comprehensive conceptualization and operationalization of the latter. This is surprising given that by their nature armed conflicts introduce contextual features that can affect fear of crime. Moreover, it is unclear if and to what extent the relationship between fear of crime and armed conflict could be shaped by the residential environment, also a significant omission given the importance of such environment in predicting fear of crime in places with ordinary 'street crime.' In this chapter I argue and find support for the hypothesis that increases in individual fear of crime are related to increases in two essential characteristics of armed conflicts: a) extreme violence and b) the presence of the military and organized armed groups. I also find evidence that collective efficacy –as a characteristic of the residential environment– attenuates fear of crime where the WOC has been intense, but it magnifies fear of crime where the WOC has not been intense. In explaining these results, I extend scholarship on armed conflicts, 'neighborhood effects' and fear of crime by drawing from international and humanitarian criminal law, the social amplification of risk framework and research on how environments influence fear of crime. I exploit a longitudinal data set collected before and during the recent Mexican 'War on Organized Crime' –a recognized armed conflict– to carry out the analyses and support my claims.

Keywords: armed conflict, Mexican ‘War on Organized Crime,’ fear of crime, collective efficacy

Introduction

Fear of crime is a significant problem in society because of its association with detrimental psychological consequences. Much of the research on fear of crime studies how it depends on two factors: 1) the individual characteristics that make people feel vulnerable, such as low socioeconomic status; and 2) the qualities of their residential context, such as the extent of social disorganization or concentrated disadvantage (for reviews see Hale, 1996; Henson and Reyns, 2015).

Surprisingly, research has mostly overlooked how fear of crime is shaped by armed conflicts or wars. This is an important omission because armed conflicts affect many regions around the world and cause great destruction. Estimates suggest that there were 30 to 50 armed conflicts and wars yearly between 1989 and 2012 throughout most regions of the world, resulting in over 850,000 deaths (Themnér and Wallensteen, 2014: 543). Additionally, legal scholars and practitioners have made great strides in conceptualizing armed conflicts and, as I show, these theoretical elements can generate rich ideas about how to test their association with fear of crime. Moreover, it is unclear if and to what extent the relationship between armed conflicts and fear of crime could be shaped by characteristics of the residential context, which researchers have found to be central to how crime is experienced in developed cities (Hale, 1996: 113-119).

In this chapter I exploit a longitudinal data set collected before and during the recent Mexican 'War on Organized Crime' (WOC) to examine 1) how fear of crime is associated with armed conflict and 2) how the residential context shapes this relationship.

Regarding objective (1), I study how fear of crime is related to the two essential characteristics of armed conflicts, defined by international and humanitarian criminal law: the presence of a) extreme violence and b) the Military and Organized Armed Groups (MOAG) (Casey-Maslen, 2014). In places with armed conflicts, research has typically focused on extreme violence to understand a variety of outcomes, while overlooking the additional and potentially independent influence of the MOAG (e.g., Caudillo and Torche, 2014). When elements of the MOAG are considered, they are operationalized as individual perceptions and not as contextual factors (e.g., Villarreal and Yu, 2017). I extend this important body of work by leveraging international humanitarian and criminal law to conceptualize and operationalize the WOC as an armed conflict that influences fear of crime as a contextual attribute.

In relation to objective (2), I study whether collective efficacy moderates the association between fear of crime and armed conflict. Collective efficacy is commonly defined as the combination of cohesiveness and normative expectations of members' behavior and it is a feature of the residential context that is often conceptualized as an indicator of community wellbeing in the United States and other developed countries (Sampson, 2012; Sampson, Raudenbush, and Earls, 1997). But research in extremely violent places in Latin America has either questioned the utility of the immediate residential context to understand fear of crime (e.g., Villarreal and Yu, 2017: 2) or argued that some of its allegedly beneficial characteristics –such as social cohesion– actually increase the perceived victimization risk (e.g., Villarreal and Silva, 2006). However, no research to date has explored how collective efficacy moderates the relationship between fear of crime and armed conflicts using the tools and concepts of the ‘neighborhood effects’ literature. In pursuing this objective, my research strives to understand how, when and for whom the immediate context matters in explaining fear of crime (Sharkey and Faber, 2014).

I find that the extreme violence and the presence of the MOAG brought on by the WOC are independently associated with increases in individual fear of crime, while collective efficacy moderates these associations. Drawing from the “social amplification of risk” framework (Jackson, 2006: 259-260; Kasperson et al., 1988), I argue that individuals interpret extreme violence and the presence of the MOAG as foreign threats and signs of a state of emergency that is beyond the community’s control. In turn, the anxiety and sense of insecurity that this generates intensifies fear of ordinary street crime.

I also find that collective efficacy attenuates and intensifies fear of crime. I re-conceptualize collective efficacy using the social amplification framework to argue that in places with extreme violence and high presence of the MOAG collective efficacy attenuates fear of crime because it constitutes a mechanism through which the community signals that it can be trusted and relied upon for moral support and to provide some sense of security or control. This is consistent with collective efficacy theory (Sampson, 2012) and research on how environments influence fear of crime in developed countries (Hale, 1996: 113-119; Jackson, 2004; Killias, 1990; Tulloch, 2003).

Contrarily, in places where the WOC has not been intense, high levels of collective efficacy amplify fear of crime because –in the absence of a foreign and extraordinary threat– collective efficacy is not interpreted as a sign of support and reassurance. Rather, it operates as a diffusion mechanism that spreads information about the few instances of violence and MOAG presence in the community, heightening awareness of these events. Thus, I specify the conditions under which collective efficacy protects individuals from detrimental factors, as well as the conditions under which collective efficacy might enhance their negative consequences.

The Mexican WOC provides a unique opportunity to study the potential association between fear of crime and armed conflict, as it features both characteristics of armed conflicts (Casey-Maslen, 2013; 2014). Key for both this conceptualization and my estimation strategy in this chapter is the geographic and temporal variability in terms of the onset and intensity of the WOC. The WOC was launched at different times in different regions of Mexico. Moreover, while some places were subject to intense armed conflict, others were excluded from it altogether. I exploit this variability across time and space in my empirical analyses to estimate how levels of fear of crime are associated with changes in violence and the presence of the MOAG and how changes in collective efficacy moderate these relationships.

I make key contributions to three specific literatures. I expand the empirical research on armed conflicts and war-like violence by drawing from legal international scholarship to improve upon previous conceptualizations and operationalizations of armed conflict. I also expand the theoretical confines of fear of crime and ‘neighborhood effects’ research by drawing extensively from the social amplification of risk framework and building upon previous work that has recognized its usefulness in these fields (Jackson, 2006: 259-260) and has made limited use of its elements (e.g., Brunton-Smith, Sturgis, and Leckie, 2018: 613). Empirically, I improve upon the common data constraints of research on collective efficacy and fear of crime by using repeated observations of individuals and communities to estimate the relationship between the variables of interest, which enables me to isolate these relationships more robustly. More broadly, my research bridges the boundaries of these three literatures (armed conflict, fear of crime, 'neighborhood effects'), building on recent important work at this intersection (e.g., Hagan et al., 2015; Villarreal and Yu, 2017) and, more generally, on a small but growing literature on neighborhood effects and armed conflict (e.g., Hagan, Kaiser, and Hanson, 2016; Kaiser and Hagan, 2018).

The Mexican 'War on Organized Crime' as an armed conflict

The *War report* –a leading annual report that registers and describes armed conflicts throughout the world– has classified the WOC in some regions of Mexico as an armed conflict (Casey-Maslen, 2013; 2014). The International Criminal Tribunal for the Former Yugoslavia established that a non-international armed conflict exists "when there is protracted armed violence between governmental authorities and organized armed groups, or between such groups within a state" (Casey-Maslen, 2014: 11). The Tribunal interpreted the term 'protracted armed violence' as intense and sustained confrontation, different from ordinary crimes, spontaneous and brief insurrections and isolated terrorist acts; and the term 'organized armed groups' as organizations with a command structure and the logistical and armament capacity to conduct military operations (Casey-Maslen, 2013; 2014). Hence, a domestic armed conflict exists when there are structured and powerful non-state groups that engage regularly in intense, military-style confrontations with similar organizations and/or with the state security forces, mainly the military. This definition also implies that armed conflicts are extra-local and extraordinary, meaning that these conditions are unlikely to be experienced in communities under normal circumstances with ordinary 'street crime' (see also Villarreal and Yu, 2017).

Two characteristics are central to this conceptualization of armed conflict: (1) extreme violence and (2) the presence and activity of the military and organized armed groups. Notably absent from this definition is the requirement that the organized armed group have a political or religious ideology or goal.

Fear of crime, armed conflict and collective efficacy

I argue that the Mexican WOC has the two main characteristics of armed conflicts: (1) extreme violence, different in nature from ordinary street crime and characterized by a sharp increase in homicides, many of which are perpetrated viciously and with military-style tactics and armament; and (2) the presence of the MOAG, such as *autodefensas* or vigilante forces, militias, DTOs and paramilitary groups.

I further argue that these characteristics signal to individuals that they live in a state of emergency brought on by foreign and extraordinary threats, a situation that is experienced as beyond the community's control and leads to more fear of ordinary crime. However, high collective efficacy signals to individuals that the community is united and that it can be trusted and relied upon to provide some sense of security or control (Brunton-Smith, Sturgis, and Leckie, 2018: 613), or at least some sense that this extraordinary state of affairs is 'manageable' (Killias, 1990). Thus, collective efficacy should attenuate the influence of armed conflicts on fear of ordinary crime, a hypothesis that is consistent with collective efficacy theory (Sampson, 2012) and research on how environments influence fear of crime in developed countries (Hale, 1996: 113-119; Jackson, 2004; 2006; Killias, 1990; Tulloch, 2003).

But I also argue that when the armed conflict is of low intensity collective efficacy should magnify fear of ordinary crime because the social and moral connections that underlie collective efficacy work to spread violence-related information, heightening awareness of these events. This aspect of collective efficacy is muted in places where armed conflicts are intense because information about extreme violence and the presence of the MOAG is widely available through other means (direct experience, mass media, etc.). Conversely, in places where the armed conflict is not intense collective efficacy is unlikely to be interpreted as a sign of support and reassurance due to the absence of a significant foreign and extraordinary threat that could catalyze these feelings. The intensification and attenuation of fear of crime through these varied processes can be understood by extending the social amplification framework (Jackson, 2006: 259-260; Kasperson et al., 1988) to study of armed conflicts and collective efficacy.

Fear of crime intensification and armed conflict

I expect fear of crime to be positively associated with extreme violence and the presence of the MOAG due to a process of *intensification*. Intensification takes place through a mechanism that combines three key features of the information emanated from the armed conflict: volume, dramatization and symbolism (Jackson, 2006: 259-260; Kasperson et al., 1988: 184-185). The Mexican WOC generates a large volume of dramatic and highly symbolic information because people are more likely to experience or have knowledge of extreme violence and the presence of the MOAG –to be victimized directly or indirectly (Covington and Taylor, 1991; Skogan, 1986)– in a context of intense armed conflict. People are also more likely to remember these dramatic and highly symbolic events and to overestimate how pervasive they are (Warr, 2000), as well as to interpret new experiences in terms of their association with these events (Kasperson et al., 1988). Individuals interpret this large volume of dramatic and symbolic information from the armed conflict as visible signs of a state of emergency beyond the community's control, which creates anxiety and fear of ordinary street crime.

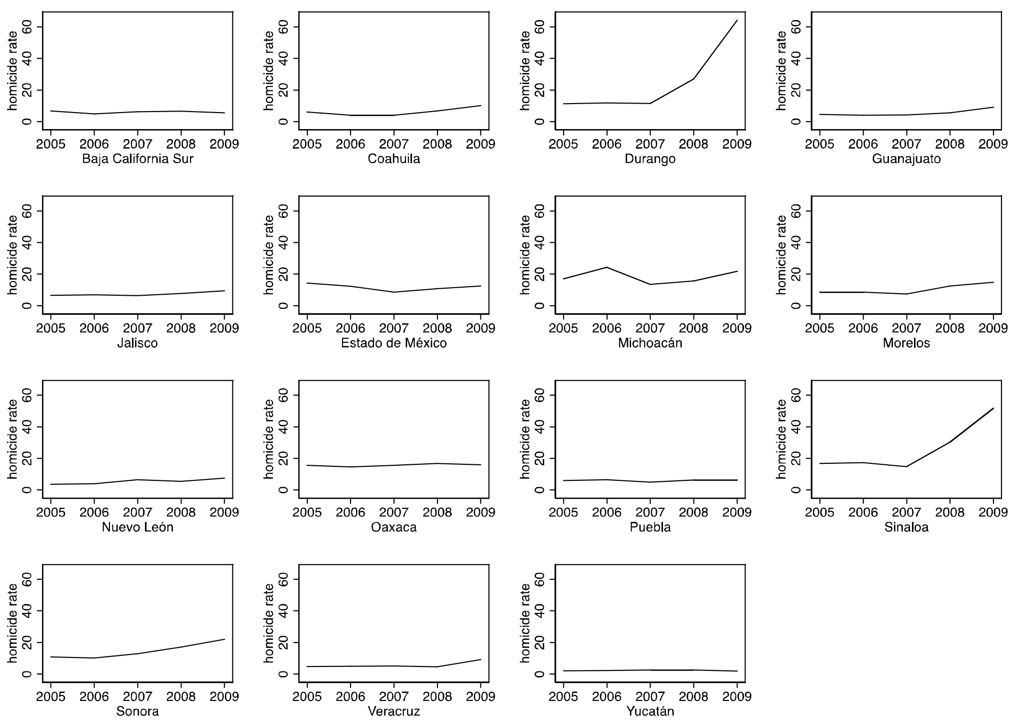
The transference mechanism linking dramatic and symbolic information about the context to fear of specific forms of ordinary crime is based on the notion that fear of crime is at least partly an expression of personal and environmental vulnerability and lack of trust and control (Jackson, 2004; 2006; Killias, 1990; Tulloch, 2003). Similar mechanisms have been proposed before. For instance, Ferraro's (1996) understanding of sexual assault (rape) as a 'master offense' among women, Innes' (2004) idea of 'signal crimes and signal disorders,' and Warr's (1990) notion of 'dangerous situations' highlight how certain crimes and situations are given more weight in calculations of victimization risks and, interpreted through the lens of vulnerability and lack of control/trust, affect how individuals perceive other crimes. I build on these ideas by studying armed conflicts and leveraging the social amplification framework (volume, dramatization and symbolism) to understand how armed conflicts affect fear of ordinary crime.

Armed conflicts generate a large volume of information because they entail extreme violence, which is characterized by large and sudden increases in homicide levels. In the Mexican case, the onset of the WOC at the end of 2006 marked the beginning of a period of extreme violence. The national homicide rate per 100,000 increased sharply after 2007 reversing its decades-long downward trend (Heinle, Molzahn, and Shirk, 2015: 3), with almost all of the increase due to drug-related violence (Molzahn, Rodriguez Ferreira, and Shirk, 2013: 6).

This national average masks great heterogeneity across time and space. Some regions in Mexico experienced more violence than many war zones (Shirk and Wallman, 2015: 1349-1350), especially those along the trafficking corridors to the United States (e.g., the Mexico-US border) and in drug-producing areas (e.g., the 'golden triangle,' state of Michoacán), but many others were not affected by the WOC (Calderón et al., 2015; Shirk and Wallman, 2015: 1354). Moreover, those regions that were exposed to the armed conflict were not so at the same time or with the same intensity (Heinle, Molzahn, and Shirk, 2015). Figure 3.1 shows this heterogeneity for those states present in the analytical sample (described below).

In addition to high levels of violence, the extreme violence that distinguishes armed conflicts also possesses a dramatic quality. Violence during the WOC often involved high-caliber weaponry (e.g., assault and anti-armor weapons, grenades, anti-aircraft missiles and armored Humvees), military-style tactics, high-impact targets (e.g., mayors and other politicians, journalists, law enforcement officers) and the deployment of commandos across large swaths of territory (Knight, 2012; Shirk and Wallman, 2015: 1351). Much of the violence was also highly symbolic and aimed at intimidating and terrorizing rival DTOs, the government and the general public (Ríos, 2015; Shirk and Wallman, 2015: 1354). It was often gruesome (e.g., beheadings, dismemberments, signs of torture), displayed openly (e.g., corpses left in public places or hanging from bridges, street gun battles) and produced to convey specific messages (e.g., corpses left with *narco*-messages) (Shirk and Wallman, 2015: 1351).

Figure 3.1 State Homicide Rates Per 100,000 (selected states, 2005-2009)



NOTE: Author's elaboration with data from INEGI (2014).

Armed conflicts also generate a large volume of dramatic and symbolic information through the presence of the MOAG, a presence that is uncommon in communities with ordinary 'street crime.' The WOC was characterized by the massive deployment of military personnel, which by 2011 had reached 45,000 troops (Calderón et al., 2015: 1456). A large proportion of these troops were sent to supplant local police or complement policing functions (Moloeznik, 2013). Similarly, DTOs, militias, vigilantes and paramilitaries became prominent in numerous places (Dell, 2015; Felbab-Brown, 2015; Phillips, 2015; Shirk and Wallman, 2015). The presence of the MOAG can intensify fear through a variety of highly symbolic mechanisms, such as the open display of force (e.g., convoys with high-caliber armament, public parades, and public displays of high-profile detainees), forms of coercion that are difficult to quantify (e.g., threats and extortions to the public) and other processes through which their presence is made known, for instance, the public display of *narco-cultura* elements (drug trafficking culture) (e.g., *narcocorridos* or narco-ballads, dressing styles, quasi-religious imagery).

The importance of considering the presence of the MOAG in addition to extreme violence to understand how armed conflicts affect fear of crime is evidenced more clearly by the fact that some regions that were not extremely violent during the WOC did experience high presence of the MOAG (Díaz-Cayeros et al., 2011). This presence could intensify fear of crime in the absence of extreme violence because individuals constantly scan their surroundings for signs of danger –including the presence of threatening 'others'– and their interpretation of these signs can increase fear of crime (Warr, 1990; see also Innes, 2004). The heavy presence of the MOAG conveys the message that the community is in a state of emergency even if this presence actually helps to control violence, since this control would be imposed by a foreign entity and might be achieved precisely through fear (Díaz-Cayeros et al., 2011). During the WOC, organized armed groups resorted to threats, intimidation, extortions and kidnappings and open displays of force to maintain control and extract economic rents (Osorio, Schubiger, and

Weintraub, 2016). The military engaged in human rights violations and other abusive practices to control crime, such as illegal searches and roadblocks and excessive use of force (Molzahn, Ríos, and Shirk, 2012: 28), which is probably why a substantive minority of Mexicans are fearful of the military (Díaz-Cayeros et al., 2011: 13).

Two additional stylized facts about the presence of the MOAG in the Mexican WOC are relevant for this study. First, despite heterogeneity in terms of their origins, approaches and goals, which makes them conceptually distinct, the boundaries between the military, militias, vigilantes, paramilitaries and DTOs are quite fluid in practice (Schuberth, 2015: 301-303) and have historically been so in Mexico (Felbab-Brown, 2015; Knight, 2012). The links between the military and DTOs also run deep, as military deserters have joined the ranks of DTOs for decades (Shirk and Wallman, 2015). Hence, there is a 'blurring' of the boundaries that separate legal and illegal or 'good' and 'bad' organizations (Menjívar, 2017), which further means that the presence and activity of any one (or all) of them is likely to be experienced as a foreign and extraordinary threat to the community.

Second, as with extreme violence, there is geographical and temporal heterogeneity in the presence of the MOAG. Estimates suggest that one third of Mexican municipalities across different regions were DTO-free at the height of the WOC (Dell, 2015: 1739). Similarly, the emergence of other organized armed groups was patterned by previous experience with vigilante mobilization and paramilitarism (Phillips, 2015), as well as by the more recent process of militarization that characterized the WOC (Moloeznik, 2013), rendering a geographical and temporal patchwork of presence and activity.

By including the presence of the MOAG as a contextual, independent predictor of fear of ordinary crime my research extends an emerging but still small body of research that has shown that homicide rates in Mexico predict fear of crime and feelings of insecurity (Gaitán-Rossi and Shen, 2018; Villarreal and Yu, 2017). It also builds on Hagan and colleagues' (Hagan et al., 2015) research in Baghdad's neighborhoods, which explores the consequences (displacement) of fear after the American Occupation of Iraq. Their goal, however, was not to investigate how this armed conflict gave rise to fear.

Collective efficacy as a social amplification mechanism

I expect collective efficacy to moderate the association of fear of crime and armed conflict. Specifically, I hypothesize that collective efficacy should *attenuate* fear of ordinary crime in places with extreme violence and high presence of the MOAG, while collective efficacy should *amplify* fear of ordinary crime where these characteristics of the armed conflict were not intense. I extend the social amplification framework and research on environmental influences on fear of crime to explicate how this moderation takes place.

Collective efficacy is defined as the linkage between social cohesion, or mutual trust, and normative expectations to intervene in favor of a collectivity (informal control) (Sampson, 2012; Sampson, Raudenbush, and Earls, 1997). It is a group characteristic that comprises aspects of interpersonal trust and network density, as well as shared norms or beliefs about the collectivity's capacity to control crime and other anti-social behavior (Brunton-Smith, Sturgis, and Leckie, 2018; Sampson, 2012).

Research looking at the relationship between fear of crime and collective efficacy broadly suggests that these factors are inversely related, consistent with collective efficacy theory. For example, research on London boroughs shows that collective efficacy lowered the effect of negative structural characteristics on beliefs and worries about crime (Brunton-Smith, Jackson, and Sutherland, 2014; see also Jackson and Gray, 2010). Similarly, collective efficacy alleviated fear of crime in three middle-sized American cities (Gibson et al., 2002) and in two Miami neighborhoods (Swatt et al., 2013). The same association has been found in research focusing on individual elements of collective efficacy. For instance, fear of crime has been shown to be inversely associated with social cohesion (Scarborough et al., 2010), individual-level generalized trust (Intravia et al., 2016) and neighborhood trust (Alper and Chappell, 2012). It has also been shown that communities where more people were willing to intervene (call the police) to curb graffiti spraying had lower levels of fear of crime (Covington and Taylor, 1991).

However, no research on fear of ordinary crime and armed conflicts has analyzed how collective efficacy moderates this relationship. To explore this moderation and in line with the social amplification framework (Jackson, 2006; Kasperson et al., 1988), I further conceptualize collective efficacy as a community signal or cue that transmits different information depending on the level of threat experienced in the community. Extending ideas on environmental cohesion and control (Hale, 1996: 113-119; Jackson, 2004; 2006; Killias, 1990; Sampson, 2012; Tulloch, 2003) to the study of armed conflicts, I argue that collective efficacy should attenuate fear of ordinary crime in places with extreme violence and high presence of the MOAG because cohesive communities that have clear expectations regarding social control signal to their members that the community can be relied upon for support, which minimizes the state of emergency that these threats generate and, ultimately, fear of crime.

The support provided in this situation can be emotional, whereby individuals interpret collective efficacy as a signal that they are not facing these extraordinary and foreign threats alone and that the community has some control over them (Brunton-Smith, Sturgis, and Leckie, 2018). But it can also manifest itself in tangible preventive actions that could minimize individuals' perceived risk of victimization. For instance, in some communities besieged by extreme violence during the Mexican WOC people grouped to travel in caravans and engaged in leisurely activities in streets closed by the local government with the goal of preventing victimization (Villarreal, 2015).

However, I also argue that when the armed conflict is of low intensity, violent events and the presence of the MOAG are unlikely to be interpreted as foreign and extraordinary threats. Under these circumstances, collective efficacy is not activated as a defense mechanism, but the social and moral connections that underlie collective efficacy would be helpful to disseminate the little information available about the armed conflict, sensitizing members of the community to it and thus amplifying fear of crime. Due to the WOC's national character and prominence, its violence is likely to resonate with communities that are not directly affected by it but that are similar –in terms of geographic location or rural status, for instance– to those communities that are being impacted by the WOC. Crime news and stories are more likely to resonate with audiences that share characteristics, experiences, and living conditions with those victimized by violence (Chiricos et al., 1997; Kaminski et al., 2010).

This argument points to the ambiguity of both social cohesion and control with regards to how crime is experienced. Albeit collective efficacy has generally been shown to protect individuals from fear of crime (see above), research on cohesion (e.g., Villarreal and Silva, 2006) and collective or institutional forms of crime control –such as the presence and activity of neighborhood watch-style organizations (e.g., Gaitán-Rossi and Shen, 2018) and the police (e.g., Innes, 2004: 349-350)– suggests that these factors can heighten perceptions of risk of victimization and feelings of insecurity. I build on these ideas to show that a process of amplification takes place in Mexican communities with high levels of collective efficacy that have been subjected to low or almost nonexistent levels of the armed conflict.

Data

I draw on the Mexican Family Life Survey (MxFLS) for most of the data in this chapter. The MxFLS uses INEGI's Primary Sample Units as its sampling frame, each of which include between 160 and 300 households in one or more contiguous blocks (nonmetropolitan localities) or rural localities (INEGI, 2009: 15-17). States were selected within each region with equal probability and Primary Sample Units were selected with equal probability within each region (Northeast, West, Central, Northwest, and South) and stratum (rural-urban). In each unit, households were selected with equal probability and every member of the selected household was interviewed.

I use the second and third waves in the main analyses because these included measures of collective efficacy. I also limit my analyses to rural (fewer than 2,500 inhabitants) and nonmetropolitan (between 2,500 and 15,000 inhabitants) localities. Localities are defined as places recognized by law or custom that have one or more households and are often delimited by physical (e.g., rivers, ravines) and cultural (e.g., highways, railroads) barriers (INEGI, 2009: 3-5). Rural and nonmetropolitan localities are small and well-defined residential places, and as such, they can be conceptualized as communities or ecological units with distinct collective properties. This claim is harder to justify in the case of urban localities with more than 15,000 inhabitants because they are more likely to enclose different residential environments, each with distinct properties. Examining small localities reduces true within-locality heterogeneity for the constructs that are aggregated from individual/household data (Hipp, 2007: 663), which reduces the likelihood that areas within each locality could differ in terms of the true value of these constructs.

I include 88 communities (176 locality-time observations) in the main analyses, which comprise the majority of the 95 rural and nonmetropolitan localities that were originally sampled in 2002. The excluded communities had fewer than twenty households surveyed in either wave, which could make their community measurements unreliable (Raudenbush and Sampson, 1999). Additionally, excluding localities with few observations can increase precision and reduce potential biases that could arise from the sampling procedure. The minimum number of households surveyed in the analytical sample per locality-time was 21 and the maximum 82, with an average of 49.65 and a standard deviation of 9.25.[9] I identify the individuals and households that were observed at both times in these communities. There were 8,520 adults

[9] Analyses in the Appendix show that the main results are robust if they are carried out with communities that did not have at least 20 households at each time and with the communities that had at least 30 households.

interviewed in both waves in these 88 communities for a total of 17,040 person-wave observations, which constitutes my analytical sample. From these 8,520, I drop 1,106 individuals with missing values (almost half of them in fear of crime) and 5 more that moved between communities.[10] The final sample includes 7,409 individuals for a total of 14,818 observations.

I complement these data with information about the homicide rate (municipality and state) and socio-demographic characteristics (municipality), which are taken from INEGI and the Mexican National Population Council (CONAPO), respectively.

Methods

I use fixed-effects models at the individual level, which in a two-wave case are equivalent to first-difference models (Vaisey and Miles, 2017). I fit main effects and interaction models, depending on the specific objective. The main effects models (objective 1) are written as follows:

$$y_{ijt} = \beta_0 + \beta_1(\boldsymbol{WOC})_{jt} + \beta_2(\boldsymbol{IC})_{ijt} + \beta_3(\boldsymbol{CC})_{jt} + \alpha_{ij} + \mu_{ijt} \qquad (1)$$

where y_{ijt} is defined as fear of crime for individual *i*, located in community *j*, at time *t*. ***WOC*** is a vector of continuous variables that captures the presence and intensity of the 'War on Organized

[10] Results imputing the missing data (Appendix) are similar to the main findings in Table 3.2. I performed multiple imputation (MI) to generate 20 sets of imputed values and then reproduced the substantive analyses averaging the parameter estimates across these imputed data sets and calculating standard errors using both the within- and between-data set variance (Allison 2002: chapter 4). The imputation model includes all the variables used in the substantive analyses, even the interaction terms and the dependent variable (White, Royston, and Wood, 2011).

Crime' in community j, at time t. $\boldsymbol{IC}$ is a vector of time-varying individual and household characteristics, $\boldsymbol{CC}$ is a vector of time-varying community characteristics (including collective efficacy), α_{ij} is a set of individual fixed effects, and μ_{ijt} is the idiosyncratic error term. In this specification, the variables in vector $\boldsymbol{WOC}$ are the key explanatory variables, while vectors $\boldsymbol{IC}$ and $\boldsymbol{CC}$ are introduced as controls. All of these variables are described in the next section.

The interaction effects models (objective 2) are specified as follows:

$$y_{ijt} = \beta_0 + \beta_1(\boldsymbol{WOC}\ \mathrm{X}\ CE)_{jt} + \beta_2(\boldsymbol{IC})_{ijt} + \beta_3(\boldsymbol{CC})_{jt} + \alpha_{ij} + \mu_{ijt} \tag{2}$$

where CE measures collective efficacy, and all other terms are the same as in Equation 1, except for $\boldsymbol{CC}$, which now excludes collective efficacy.

These fixed-effects models discard variation between individuals, which makes estimates less efficient, but also less susceptible to be biased due to unobserved characteristics associated with the predictors and the dependent variable that have constant values and associations with the outcome over time (Allison, 2009).[11] My models also implicitly control for unobserved between-community variation because all the individuals in my analytical sample are nested within communities (Andrews, Schank, and Upward, 2006). Hence, they compare an individual's fear of crime level in the years prior to the WOC to the same individual's fear of crime level during the WOC, net of unobserved and time-invariant individual and community characteristics that could be associated with the armed conflict and fear of crime. To control for

[11] Random-effects models render substantially similar results than the main analyses with fixed-effects (Appendix).

characteristics that do change over time, I include a comprehensive set of individual, household and community characteristics (vectors **IC** and **CC**). These characteristics make this a robust estimation approach and a stringent test of the hypotheses put forth in this chapter. The significance level is set at 5 percent for all the analyses and standard errors are clustered at the individual level.[12]

Variables and measurements

The outcome of interest is *fear of crime* at the individual level, which is measured as the combination of two Likert-type items that ask adults how afraid they are (0=not scared, 1=a little scared, 2=scared, 3=very scared) of being assaulted or robbed during the day and at night. They measure fear of crime with high internal consistency (Cronbach's $\alpha = 0.85$).

The main predictors are the two main characteristics of armed conflicts. I use two different operationalizations to capture the first characteristic (*extreme violence*), namely the *municipal* and *state homicide rates*, which I calculate using official homicide counts from vital statistics and census data (INEGI, 2014). The census is conducted every ten years, so I use the 2000 and 2010 waves, as well as the 2005 official population estimation, to linearly interpolate the population count for the rest of the years, a common strategy when the Mexican census is used (e.g., Caudillo and Torche, 2014). I then use the homicide rates for the first year of the wave (2005 for wave 2 and 2009 for wave 3) as predictors.

[12] I present the main analyses with the standard errors clustered at the community level in the Appendix. As expected, the standard errors are larger but the key coefficients remain significant.

I use three variables to measure the second characteristic of armed conflicts (*the presence of the military and organized armed groups*) at the community level. The survey asks household representatives if there is presence (0=No; 1=Yes) in the community of (1) *military reserves or soldiers in the streets*, (2) *guards, paramilitary and/or armed groups* or (3) *armed neighbors*. These variables are moderately correlated at the community level (r = from .26 to 0.41, $p < .001$) and have relatively high internal consistency ($\alpha = .58$). They measure the presence of the military and a broad range of organized armed groups, such as vigilantes, paramilitary groups, private guards (militias) and DTOs.

Collective efficacy is the community-level moderator and it is measured following Sampson and colleagues (Sampson, Raudenbush, and Earls, 1997). It combines the concepts of social cohesion and trust and informal control. <u>Social cohesion and trust</u> is measured by combining four Likert-type scale items asked to a household representative. The survey asked if the respondent completely disagreed (1), disagreed (2), agreed (4) or completely agreed (5) with the following statements ('Do not know' answers were reclassified as (3) 'neither disagree nor agree'): 'This community is really close together,' 'People around here are willing to help their neighbors,' 'People from this community share the same values' and 'People from this community are trustworthy.' The four items have high internal consistency at the community level ($\alpha = 0.93$).

Similarly, <u>informal control</u> is measured using the following items asked at the household-level: how likely is it (1=not likely; 2=not very likely, 4=likely; 5=very likely; 'Do not know' answers were reclassified as 3=neither unlikely nor likely) that your neighbors in the community would do something about: a group of youths who had skipped classes and was wandering around in the street; a group of youths who was spraying graffiti; a youth being disrespectful to an adult; someone being threatened or beaten in a fight in front of your house; the closest police station being shut down due to budget cuts. These items have high internal consistency at the community level ($\alpha = 0.92$). Social cohesion and trust and informal control are strongly correlated at the community-level ($r = 0.70$, $p < .001$) and also have high internal consistency ($\alpha = .82$).

I follow the 'ecometrics' approach to generate more precise community-level estimates of collective efficacy and presence of the MOAG, a common strategy in 'neighborhood effects' research (Raudenbush and Sampson, 1999). I use three-level item-response models with items nested within households nested within communities and then compute each variable's score for each community using the Empirical Bayes (EB) residuals.[13] One potential issue with combining household-level values to generate community-level predictors is that the community-level variable might be highly sensitive to extreme household values. In this case, detected community influences might be driven by their household analogues. To exclude this possibility and to show that these are truly contextual influences, I include the household perception of the MOAG and collective efficacy as controls.

[13] As shown in the Appendix, the results using simple community averages for collective efficacy and the MOAG are very similar to those presented with EB estimates in Table 3.2.

I also control for an array of time-changing individual-, household- and community-level variables that previous theory and empirical findings suggest could be connected to fear of crime and the main predictors and moderator. People are more afraid when they perceive themselves at a physical disadvantage and/or believe that they are more likely to be victimized and to experience such victimization as more consequential than other people. Some of the factors that have been linked to fear of crime based on these arguments are gender, age, race, education, income and prior victimization (Ferraro, 1996; Hale, 1996; Henson and Reyns, 2015; Skogan, 1986; 1990).

Hence, I control for age, marital status, education and employment at the individual level. At the household level, I include the number of children in the household (less than 15 years old) and indicator variables of whether the household's house has solid (i.e., not dirt) floors, indoor plumbing, and a private toilet or electricity; whether the household has more than two people per room; whether the household is female-headed; whether at least one adult in the household earns more than 2 minimum wages per day, has a middle-school education or is employed or has been so in the previous year; whether there is at least one member of the household that identifies as indigenous or speaks an indigenous language; and whether at least one member of the household has been the victim of a crime in the previous two years (kidnapping, harassment/sexual abuse, robbery/assault, and bodily injury), or if the household's home, business or plot/land has been forcefully broken into in the same period. I also add two controls for whether the household owns the house and whether it owns a second land asset.

As discussed above, prior research in the United States has also shown that the conditions of the immediate residential context are related to individual fear of crime. In addition to collective efficacy, the variables that have been relied upon to measure this context mirror those used to capture individual vulnerability, such as concentrated disadvantage –which usually includes poverty, public assistance, female-headed households, unemployment, number of children in the household and African-American or Latino concentration– and community disorder and crime (Covington and Taylor, 1991; Hale, 1996: 113-119; Henson and Reyns, 2015; Skogan, 1990).

I aggregate all of the socioeconomic and victimization household indicators discussed before to the community level to generate proportions of households in each community-wave that feature those characteristics, an approach that has been useful in places where census data at small levels of aggregation are not available or cannot be merged with survey data (e.g., Zhang, Messner, and Zhang, 2017). Given the preponderance of age in the fear of crime literature, I also include the average age in the community. The variables that I use to measure socioeconomic status (or concentrated disadvantage) are based on the American literature on fear of crime and neighborhoods, but also on the Mexican context. To tap into this dimension, CONAPO created a marginality index for households, which I include at the municipality level as an additional control. Since it is based on the census, it is only available in 2000, 2005 (estimation) and 2010. I linearly interpolate the rest of the years and include the first year of each wave (CONAPO, 2000; 2005; 2010).

Lastly, I control for *physical and social disorder* with items that measure the presence of abandoned buildings, houses or businesses (0=No; 1=Yes) and street gangs (0=No; 1=Yes) in the community. I include these variables at the community- and household-level.

Results

Table 3.1 shows summary statistics of all the variables at the individual-, household- and community-level across time. Fear of crime is relatively low in these data. On a scale from 0 to 6, with low values indicating little fear of crime and high values indicating very high fear of crime, the average is approximately 1 in both periods. But there was an increase of 17 percent between waves. Albeit expected given the onset of the WOC, this considerable increase in a relatively short period merits further investigation. Also consistent with this expectation are the increases across time of the municipal and state homicide rates and the presence in the community of the army and organized armed groups, as well as some community crime-related controls such as crime victimization and the presence of abandoned buildings and local gangs. Community collective efficacy remains relatively stable across time, as do the socioeconomic controls at the individual-, household- and community-levels, with the ones that increased markedly being the result of the passage of time. For example, the sample in wave 3 is older, more educated and includes fewer children.

Table 3.1 Descriptive Statistics[a]

Variable	Wave 2 (2005-2006)				Wave 3 (2009-2012)			
	Mean	SD	Min.	Max.	Mean	SD	Min.	Max.
Outcome								
Fear of crime	0.86	1.45	0	6	1.06	1.63	0	6
Predictors								
Homicide rate (municipality)	8.87	9.71	0	50.91	13.32	14.07	0	87.81
Homicide rate (state)	8.88	4.90	2.17	17.12	12.48	9.55	2.37	34.19
Military and organized armed groups	0.11	0.12	0	0.50	0.18	0.18	0	0.87
Moderator								
Collective efficacy	8.62	2.70	0	13.88	8.51	2.54	2.54	15.86
Individual controls[b]								
Age	39.67	17.52	15	101	43.88	17.51	17	105
Marital status	0.67	0.47	0	1	0.70	0.46	0	1
Education	1.46	1.00	0	4	1.55	1.07	0	4
Employment	0.50	0.50	0	1	0.54	0.50	0	1
Household controls[c]								
Floors	0.80	0.40	0	1	0.88	0.32	0	1
Sewage	0.36	0.48	0	1	0.39	0.49	0	1
Toilet	0.60	0.49	0	1	0.65	0.48	0	1
Electricity	0.98	0.15	0	1	0.97	0.18	0	1
Indigenous	0.26	0.44	0	1	0.28	0.45	0	1
Female headed	0.21	0.41	0	1	0.27	0.44	0	1
Middle school	0.30	0.46	0	1	0.41	0.49	0	1
Income	0.34	0.47	0	1	0.34	0.48	0	1
Employment	0.89	0.32	0	1	0.89	0.31	0	1
People per room	0.54	0.50	0	1	0.53	0.50	0	1
Children	1.42	1.48	0	8	1.29	1.39	0	13
Home ownership	0.84	0.36	0	1	0.85	0.36	0	1

Table 3.1 (Continued)

Second asset	0.24	0.43	0	1	0.26	0.44	0	1
Crime victimization	0.02	0.10	0	2	0.03	0.13	0	2
Abandoned buildings	0.18	0.38	0	1	0.23	0.42	0	1
Gangs	0.13	0.34	0	1	0.18	0.38	0	1
Collective efficacy	32.12	6.57	9	45	32.02	6.77	9	45
Military and organized armed groups	0.10	0.35	0	3	0.18	0.46	0	3
Community controls[d]								
Age	29.30	3.42	21.28	38.31	29.95	3.43	22.22	39.14
Floors	0.81	0.20	0.06	1	0.88	0.14	0.08	1
Sewage	0.38	0.38	0	1	0.42	0.37	0	1
Toilet	0.62	0.29	0	1	0.66	0.29	0	1
Electricity	0.98	0.03	0.84	1	0.96	0.04	0.86	1
Indigenous	0.25	0.32	0	1	0.27	0.31	0	1
Female headed	0.23	0.09	0.02	0.49	0.29	0.09	0.08	0.56
Middle school	0.29	0.15	0	0.64	0.39	0.15	0.03	0.71
Income	0.33	0.19	0	0.81	0.32	0.16	0.02	0.67
Employment	0.87	0.09	0.49	1	0.86	0.08	0.63	1.00
People per room	0.57	0.15	0.14	0.83	0.55	0.14	0.18	0.83
Children	1.35	0.43	0.72	3.08	1.21	0.39	0.48	2.91
Home ownership	0.82	0.12	0.54	1	0.83	0.10	0.52	1
Second asset	0.23	0.16	0	0.67	0.25	0.16	0	0.93
Marginality (municipality)	-0.47	0.78	-1.91	1.96	-0.48	0.78	-1.89	1.84
Crime victimization	0.06	0.06	0	0.25	0.08	0.07	0	0.44
Abandoned buildings	0.19	0.15	0	0.82	0.23	0.15	0	0.71
Gangs	0.14	0.14	0	0.79	0.18	0.14	0	0.50

ABBREVIATIONS: Max. = maximum; Min. = minimum; SD = standard deviation.

[a] means for dummy variables can be interpreted as the proportion coded of the sample 1 on that indicator

[b] Individual *N* (wave 2) = 7,409; (wave 3) = 7,409

[c] Household *N* (wave 2) = 3,312; (wave 3) = 3,658

[d] Community *N* (wave 2) = 88; (wave 3) = 88

The first two models in Table 3.2 test the direct association of fear of crime with extreme violence and the presence of the MOAG. These models differ in their operationalization of extreme violence. The first model includes the municipal homicide rate, while the second model includes the state homicide rate. As hypothesized, the coefficients on the municipal and state homicide rates are statistically significant and positive. An increase of one homicide in the municipal homicide rate across time is associated with an increase of approximately 0.006 in the fear of crime scale within individuals, on average. Similarly, a one-homicide increase in the state homicide rate across time is associated with an increase of 0.01 in the fear of crime scale, on average, also within individuals.

The coefficient on the presence of the MOAG is also statistically significant and positive in both models. A within-community increase of 0.1 in the MOAG presence scale is associated with an average within individual increase of about 0.2 in the fear of crime scale. This is a large association considering that the average of fear of crime is approximately 1. Overall, these results suggest that increases in violence and the presence of the MOAG are associated with increases in fear of crime.

Models in columns (3) and (4) test the moderating effect of collective efficacy. Again, these models differ in their operationalization of extreme violence, as column (3) includes the municipal homicide rate and column (4) the state homicide rate. The coefficient on the interaction of collective efficacy and the municipal homicide rate is not significant. However, the coefficient on the interaction term of the state homicide rate and collective efficacy is significant,

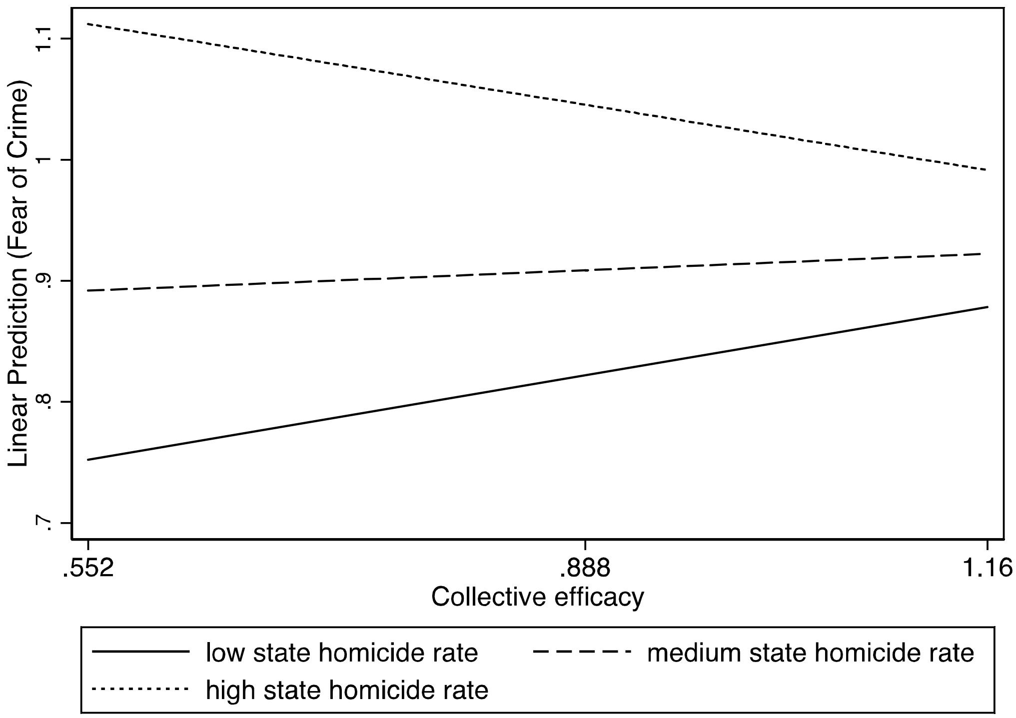
Table 3.2 Results of Fixed-Effects Models Predicting Fear of Crime

Variable	(1)	(2)	(3)	(4)
Municipal homicide rate	0.00608***		0.00828	
	(0.00110)		(0.00441)	
State homicide rate		0.00983***		0.0331***
		(0.00175)		(0.00828)
Military and organized armed groups	1.926**	1.983**	7.462**	5.705**
	(0.609)	(0.613)	(2.202)	(2.121)
Collective efficacy X Municipal homicide rate			-0.00208	
			(0.00468)	
Collective efficacy X State homicide rate				-0.0230**
				(0.00797)
Collective efficacy X Military and Organized Armed Groups			-7.081**	-5.062*
			(2.581)	(2.501)
Collective efficacy	-0.0271	-0.0100	-0.0882	0.300
	(0.115)	(0.116)	(0.145)	(0.190)
Constant	-1.930	-1.797	-1.844	-1.937
	(1.475)	(1.409)	(1.442)	(1.433)
R-squared	0.047	0.047	0.049	0.050
N (individuals X waves)	14,818	14,818	14,818	14,818

NOTE: Results presented are coefficients with standard errors clustered at the individual level in parentheses. All the models control for the individual, household and community controls in Table 3.1.
ABBREVIATIONS: MOAG = military and organized armed groups.
*** p<0.001, **p<0.01, *p<0.05 (two-tailed tests)

a finding that is consistent with the expectations expressed above and the regional nature of armed conflicts.

Figure 3.2 Association Between Low, Medium and High State Homicide Rate and Fear of Crime at Low, Medium and High Levels of Collective Efficacy

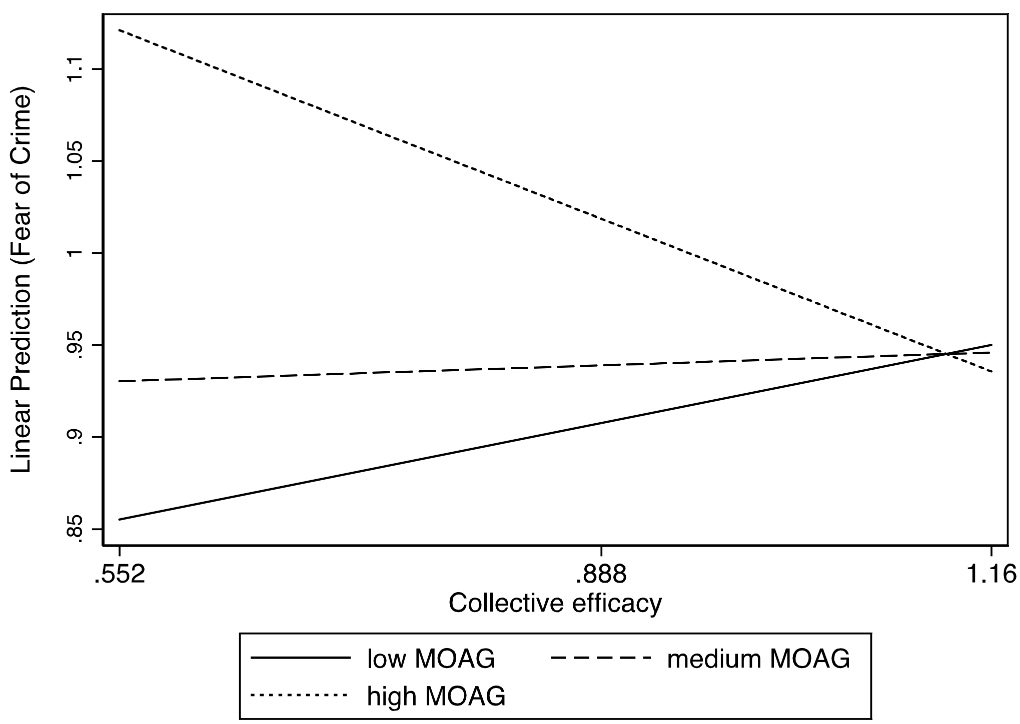


NOTE: low, medium and high levels are defined as the 10th, 50th and 90th percentiles of each variable's distribution.

Figure 3.2 presents the significant interaction between the state homicide rate and collective efficacy graphically. The dotted line shows the downward association between extreme violence at the state level and fear of crime for hypothetical individuals living in communities with different collective efficacy levels. The slope confirms the hypothesis that collective efficacy mitigates the influence of extreme violence at the state level on individual fear of crime.

Conversely, the upward trajectory of the solid line shows that collective efficacy enhances the influence of low state homicide level on fear of crime. Specifically, a hypothetical change from 1 SD below the mean to 1 SD above the mean in collective efficacy is associated with a 0.1 increase in the fear of crime scale in places with low state homicide rate. The same change in collective efficacy is associated with a decrease of 0.1 in the fear of crime scale in places with high state homicide rate. Again, considering that the average of fear of crime is approximately 1 these are relatively large influences.

Figure 3.3 Association Between Low, Medium and High Presence of the Military and Organized Armed Groups and Fear of Crime at Low, Medium and High Levels of Collective Efficacy



NOTE: low, medium and high levels are defined as the 10th, 50th and 90th percentiles of each variable's distribution.
ABBREVIATIONS: MOAG = military and organized armed groups.

Columns (3) and (4) also show that the interaction between the presence of the MOAG and collective efficacy is significant. Figure 3.3 shows the result for the state homicide rate (column 4) graphically. Just as in Figure 3.2, the dotted and solid lines have a downward and upward slope, respectively. This confirms the attenuation of fear of crime when the presence of the MOAG is high, as well as the intensification of fear of crime when the presence of the MOAG is low, for hypothetical individuals living in communities with increased collective efficacy. A hypothetical change from 1 SD below the mean to 1 SD above the mean in collective efficacy is associated with an increase of 0.08 in the fear of crime scale in places with low MOAG presence and a decrease of 0.15 in the same scale in places with high MOAG presence.

It could be reasonably argued that more fearful households would be more sensitive to high levels of the MOAG or low levels of collective efficacy or that the association between fear of crime and extreme violence and the presence of the MOAG might be a function of prior fear of crime levels. Communities that are more fearful might pressure the government to send the military in or might be more likely to form vigilante, militia or paramilitary groups. DTOs might be emboldened to boost their position in the region if this fear paralyzes communities, too. In turn, the heightened presence of the MOAG could reasonably lead to extreme violence.

I use two tests to show that the main results are robust to these potential problems. First, I re-generate the community averages of the MOAG and collective efficacy excluding each particular household. Thus, under this specification, each household in the same community-wave now has a different score on these community variables that was calculated without considering the household's perception of these factors, which reduces single source bias (Campbell and Fiske, 1959) and alleviates concerns that the contextual influences could be driven by the perception of more fearful households or individuals. Analyses in the Appendix show that the results are similar to those found in the main analyses. Second, I use Vaisey and Miles' (2017) treatment selection test for continuous variables. For this, I leverage the first wave of the MxFLS (2002) and regress the predictors at wave 3 on (1) fear of crime at wave 2 and (2) fear of crime at wave 2 plus fear of crime at wave 1. If (1) is significantly related to the predictors at the following wave controlling for (2), which is conceptualized as a proxy for the fixed effect, then the relationship between fear of crime and the predictors (extreme violence and the presence of the MOAG) detected in the main models would in fact be capturing the effect of prior fear of crime on the predictors. There is no evidence of this spurious relationship, as shown in the Appendix.

Discussion

The Mexican 'War on Organized Crime' can be conceptualized as an armed conflict with two essential characteristics: extreme violence and the presence of the military and organized armed groups. The dataset and methodological approach I use in this chapter enable me to examine how changes in these factors are related to how people experience ordinary crime. In line with my expectations, I show that these two characteristics of the WOC are independently associated with increases in fear of crime. I argue that the presence of extreme violence and the MOAG is interpreted as a foreign and extraordinary threat that signals to individuals that they live in a state of emergency beyond the community's control, creating anxiety and fear of ordinary crime, even after controlling for ordinary crime victimization.

These findings show that extreme violence is an important predictor of fear of crime, which is consistent with claims that exposure to violence has a host of negative consequences (e.g., Caudillo and Torche, 2014). It also supports the more specific claim that in Mexico and probably in other places with armed conflicts, fear of crime is more connected to regional events and processes than in United States' neighborhoods (Villarreal and Yu, 2017). But I also find that fear of crime has a positive association with the contextual presence of the MOAG independent of violence. This points to the importance of fully conceptualizing and operationalizing armed conflicts, as it shows that armed conflicts influence how crime is experienced not just through the violence that they generate. Extending the social amplification framework allows me to explain the mechanisms through which this presence influences fear of crime.

I also show that people's residential context is important in shaping how the Mexican WOC was experienced, a conclusion that is supported by my finding that collective efficacy moderates the relationship between the WOC and fear of crime. In places where the WOC was intense, collective efficacy signals to individuals that the community can be trusted and relied upon to provide some sense of security or control, which reduces anxiety and attenuates fear of crime. This is consistent with collective efficacy theory as developed in the United States and other developed countries, attesting to the construct's cross-cultural resilience (Sampson, 2012).

Contrarily, in places where the WOC was not intense, high levels of collective efficacy amplify fear of crime. I argue that this is because collective efficacy operates as a diffusion mechanism that spreads information about the few instances of violence and MOAG presence in the community, heightening people's awareness of these factors. I argue that the lack of a foreign and extraordinary threat deactivates collective efficacy's defense function while activating its capacity to disseminate information and sensitize individuals to violence-related events. This finding can be explained by reframing collective efficacy as a community signal that transmits different information depending on whether the community is under threat or not, in line with social amplification theory.

This result can be further interpreted in one of two ways. It could be argued that this is an example of 'negative' collective efficacy. Just as social capital (Portes, 1998; see also Cerdá and Morenoff, 2007: 5), collective efficacy could be a 'mixed blessing' that sometimes has detrimental consequences for communities. But it could also be interpreted as an extension of the protective quality of collective efficacy. Research has found that fear of crime can be functional, as it can motivate individuals to exercise precaution and solve problems without undermining their quality of life (Jackson and Gray, 2010). Collective efficacy might be amplifying functional fear of crime in these places where the Mexican WOC was not intense. In this case, although collective efficacy would not be functioning as a defense mechanism it would allow fear of crime to function as a warning sign for the potential intensification of the armed conflict. In either case, my research extends prior work on collective efficacy by going beyond the question of whether they influence fear of crime or not and rather focusing on understanding how, when and for whom it matters (Sharkey and Faber, 2014).

Research outside of Western, developed cities has called into question the relevance of collective efficacy. For instance, research in Tianjin, China (Zhang, Messner, and Zhang, 2017) suggests that endemic forms of social control might diminish collective efficacy's role in shaping how individuals experience crime. However, I show that even though collective efficacy does not have a direct association with fear of crime, it does shape it indirectly in ways both predicted and not predicted by collective efficacy theory. By doing this, my research also adds to the nascent literature that has examined concepts born out of the neighborhood effects literature in places with armed conflicts or wars, such as Hagan and colleagues' analysis of legal cynicism in Iraq (Hagan, Kaiser, and Hanson, 2016; Kaiser and Hagan, 2018).

This chapter has several limitations that further research should address. First, due to data constraints, it was not possible to merge official community-level data on socioeconomic and demographic factors to the survey from which the measures of fear of crime, presence of the MOAG and collective efficacy were drawn. As explained in the data section, however, this limitation is not unique to the present study. Second, I was only able to use two waves of data. Although more than two data points are preferable to establish a trend (Vaisey and Miles, 2017), the data used in this study are still an improvement over cross-sectional data, which are the basis for most research on fear of crime and collective efficacy.

Fear of crime, armed conflicts and collective efficacy are intensely studied phenomena that have not been previously analyzed together in a way that exploits recent theoretical and empirical gains in each of these fields. This is surprising given fear of crime's effects on displacement (Hagan et al., 2015) and collective efficacy's prominent place in the 'neighborhood effects' literature (Sampson, 2012). This study is an attempt to bridge the gaps between these fields. In doing so, it reveals that fear of ordinary crime is associated with armed conflicts and that collective efficacy moderates this relationship in expected and unexpected ways.

4
Conclusion

Violent places can profoundly shape people's lives. Most of what we know about how these places affect our lives comes from studies in developed countries, particularly the United States. Yet the social, economic, and criminological conditions of communities in these countries are not representative of the conditions in developing countries, many of which experience widespread and extreme violence as a result of organized crime and armed conflict. The consequences of such violent places for individuals and communities remain understudied.

In this dissertation I examine how violence affects (1) cognitive performance, (2) weight gain, and (3) fear of crime, before and during the Mexican 'War on Organized Crime' (WOC), a militarized strategy to control drug trafficking organizations (DTOs). In the first study I show an inverted U-shape impact of violence on the cognitive skills of children. Based on the notions of normalization and desensitization, I argue that homicide rises are associated with increases in cognitive scores, but there is an inflection point in the level of homicides beyond which cognitive scores decrease substantially. Homicide levels beyond said inflection point are associated with the most extreme violence derived from the Mexican conflict.

In the second study, I examine the relationship between environmental violence and weight gain. I show large increases in weight due to violence, particularly among those with high socioeconomic status, women, and young adults. I argue that these groups have experienced larger weight gains as a result of violence because they are already at high risk of being overweight or obese and/or have been disproportionately involved in –or affected by– the extreme violence of the WOC.

In the third and final study I analyze the relationship between armed conflict and fear of crime by drawing from the social amplification of risk framework. I show that people became more fearful as violence and the presence of the military and organized armed groups increased. I also show that collective efficacy shapes this relationship: in those places where the conflict has been intense, collective efficacy is associated with less fear of crime, whereas collective efficacy is related to higher fear of crime in places where the conflict has been mild or nonexistent.

Each of these studies makes independent contributions to several literatures. Collectively, they contribute to a better understanding of the consequences and responses to environmental violence in places outside of developed countries, particularly in contexts where organized violence and conflict are present. They point to new and interesting directions for future research in these settings. For instance, I have argued that people might react differently to violence in these contexts, not only because of high average levels of violence but also due to institutional and cultural understandings of –and reactions to– violence. Specifically, I have argued that violence has to some degree become normalized in Latin America and Mexico, which helps explain a different type of relationship found in this context between environmental violence and cognitive performance. Other short-term outcomes might be influenced in similar ways in other places where the levels and experience of violence is comparable to Mexico's, particularly in Latin America, Asia, and Africa.

I have also argued that fear of crime is key to understanding how environmental violence affects cognitive performance and weight gains. Moderate fear can motivate vigilance, attentiveness, and a problem-solving attitude that could have some beneficial spillover effects, such as better cognitive performance. But high levels of fear and the anxiety and distress caused by extreme violence can prove overwhelming and unmanageable, leading to symptoms of posttraumatic stress disorder and lower cognitive performance. Even low or moderate fear can have detrimental consequences and its 'beneficial' effects might dissipate after a few weeks or months. For instance, long-term exposure to environmental violence is predictive of weight gain and fear of crime could be one of the mechanisms that explain this relationship.

My study on fear of crime shows that it is affected by conflict, supporting the argument that fear could be a pathway connecting environmental violence with cognitive performance and weight gain. Moreover, these mechanisms could be pathways to numerous other relevant individual and community outcomes beyond cognitive performance and weight gains.

This study has two more important implications for our understanding of organized violence and conflict in Mexico and beyond. First, by showing that the presence of the military and organized armed groups shapes fear of crime independently of the violence that these groups generate, my research suggests that conflicts and organized violence might have a larger impact on important outcomes such cognitive performance and weight gain than previously reported. In prior studies, conflict has been measured as the amount of violence. This is a reasonable proxy, but –as I show– one that probably underestimates the total impact of conflict and organized violence. Second, my findings suggest that collective efficacy can be a double-edged sword in developing countries experiencing conflict. It can attenuate the impact of the conflict, but it can also magnify the detrimental psychological consequences of violence. The community factors that can shape how violence is experienced in places with conflict have been understudied. My work on collective efficacy suggests that communities might react in ways that are both predictable and unpredictable by the literature on 'neighborhood effects' in countries where some regions are experiencing conflict and extreme organized violence.

Ultimately the conflict that Mexico has experienced has had negative consequences for children, adults, and communities. In the case of weight gains, this impact appears to be more consequential than in the United States and other developed countries. This highlights one of the reasons why conducting research in distinct settings is important. Even if the direction of the association between violence and a given outcome is the same as in previously investigated places, the magnitude of the relationship can shed new light on the relevance of this factor.

Social scientists have recognized the importance of residential environments in people's wellbeing. Violence is one of the main threats to this wellbeing, yet most of what we know about how violent environments affect people comes from research on a limited range of environments. My work shows that broadening this range can confirm the relevance of violence while demonstrating that in a general context of conflict, violence can have different types of relationships and magnitudes with outcomes that have been explored in developed countries.

Appendix

Supplemental Tables and Figures

1

Environmental violence and children's cognitive performance in Mexico

Table A.1 Fixed-Effects Models of Municipal and State Homicides Predicting Cognitive Scores (with homicides in each month introduced as separate terms)

Homicides	Municipal		State	
	(1)	(2)	(1)	(2)
t - 1	0.033	0.034*	0.010	0.009
	(0.023)	(0.020)	(0.007)	(0.008)
VIF	42.27	42.56	157.18	170.75
t - 1 (sq)	-0.00053**	-0.00063***	-0.00005	-0.00004
	(0.0002)	(0.0002)	(0.00003)	(0.00003)
VIF	19.79	21.22	82.93	86.14
P-value for U-test	0.076	0.046	0.073	0.13
t - 2	0.034	0.032	0.023**	0.019*
	(0.027)	(0.027)	(0.010)	(0.010)
VIF	38.06	38.20	159.56	182.17
t - 2 (sq)	-0.00034*	-0.00035*	-0.00007	-0.00005
	(0.0002)	(0.0002)	(0.00004)	(0.00004)
VIF	18.73	18.89	86.78	102.70
P-value for U-test	0.103	0.121	0.127	0.27
t - 3		0.030**		0.006

Table A.1 (Continued)

		(0.015)		(0.009)
VIF		29.08		174.52
t - 3 (sq)		-0.00013**		-0.00004
		(0.00006)		(0.00003)
VIF		7.25		76.18
P-value for U-test		0.025		0.250
P-value for F-test	0.000	0.000	0.032	0.021
R^2	0.31	0.31	0.31	0.31
N	16,021	16,021	16,021	16,021

NOTE: Results presented are coefficients with standard errors clustered at the municipal- and state-level in parentheses, depending on the analysis. All the models include municipality by wave, calendar year, and month fixed-effects and control for the individual and household controls in Table 1.1.
ABBREVIATION: VIF = Variance Inflation Factor.
*** p<0.01, **p<0.05, *p<0.10 (two-tailed tests).

Table A.2 Generalized Linear Fixed-Effects Models (with logit link) of Municipal and State Homicides Predicting Cognitive Scores

Homicides	Municipal			State		
	(1)	(2)	(3)	(1)	(2)	(3)
t - 1	0.008			0.004***		
	(0.006)			(0.0016)		
t - 1 (sq)	-0.0001**			-0.00002***		
	(0.00005)			(0.000005)		
t - (1 + 2)		0.007*			0.004***	
		(0.0035)			(0.001)	
t - (1 + 2) (sq)		-0.00004***			-0.000007***	
		(0.00002)			(0.000002)	
t - (1 + 2 + 3)			0.005**			0.003***
			(0.002)			(0.0007)
t - (1 + 2 + 3) (sq)			-0.00002***			-0.000003***
			(0.000006)			(0.0000008)
N	16,021	16,021	16,021	16,021	16,021	16,021

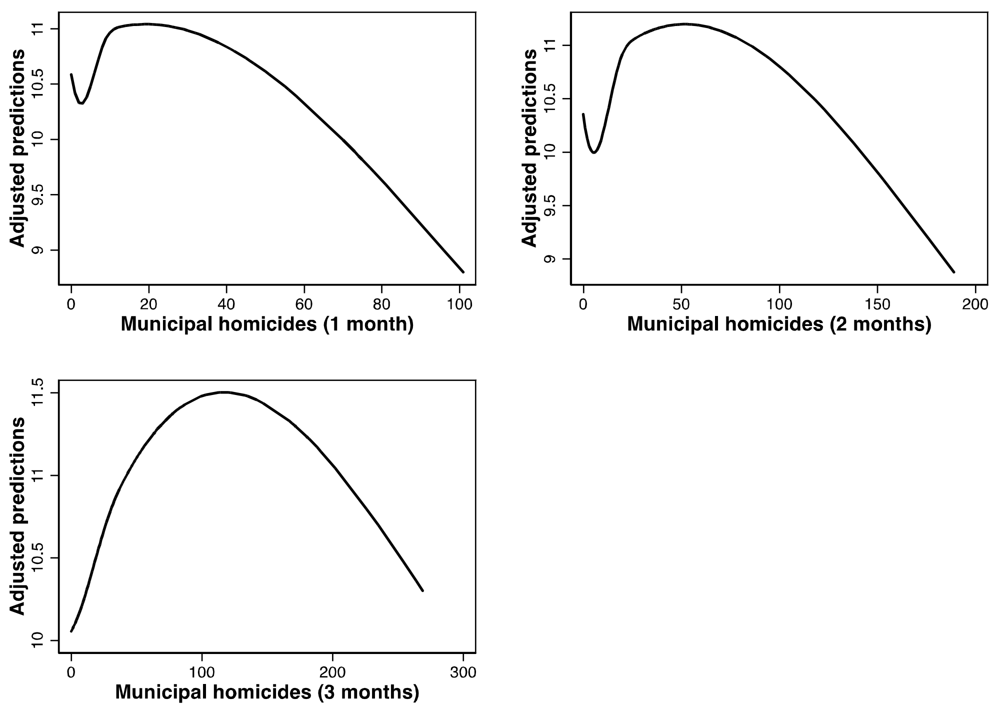
NOTE: Results presented are coefficients with standard errors clustered at the municipal- and state-level in parentheses, depending on the analysis. All the models include municipality by wave, calendar year, and month fixed-effects and control for the individual and household controls in Table 1.1.
*** p<0.01, **p<0.05, *p<0.10 (two-tailed tests).

Table A.3 Fixed-Effects Models of Municipal and State Homicides Predicting Normalized Cognitive Scores (by age and wave)

Homicides	Municipal			State		
	(1)	(2)	(3)	(1)	(2)	(3)
t - 1	0.002			0.001**		
	(0.001)			(0.0003)		
t - 1 (sq)	-0.00003**			-0.000003***		
	(0.00001)			(0.000001)		
t - (1 + 2)		0.0015*			0.001***	
		(0.0008)			(0.0003)	
t - (1 + 2) (sq)		-0.00001***			-0.000002***	
		(0.000004)			(0.0000005)	
t - (1 + 2 + 3)			0.001**			0.0006***
			(0.0005)			(0.0001)
t - (1 + 2 + 3) (sq)			-0.000004***			-0.0000007***
			(0.000001)			(0.0000002)
P-value for U-test	0.086	0.029	0.010	0.005	0.003	0.001
P-value for F-test	0.000	0.002	0.002	0.024	0.009	0.002
R^2	0.17	0.17	0.17	0.17	0.17	0.17
N	16,021	16,021	16,021	16,021	16,021	16,021

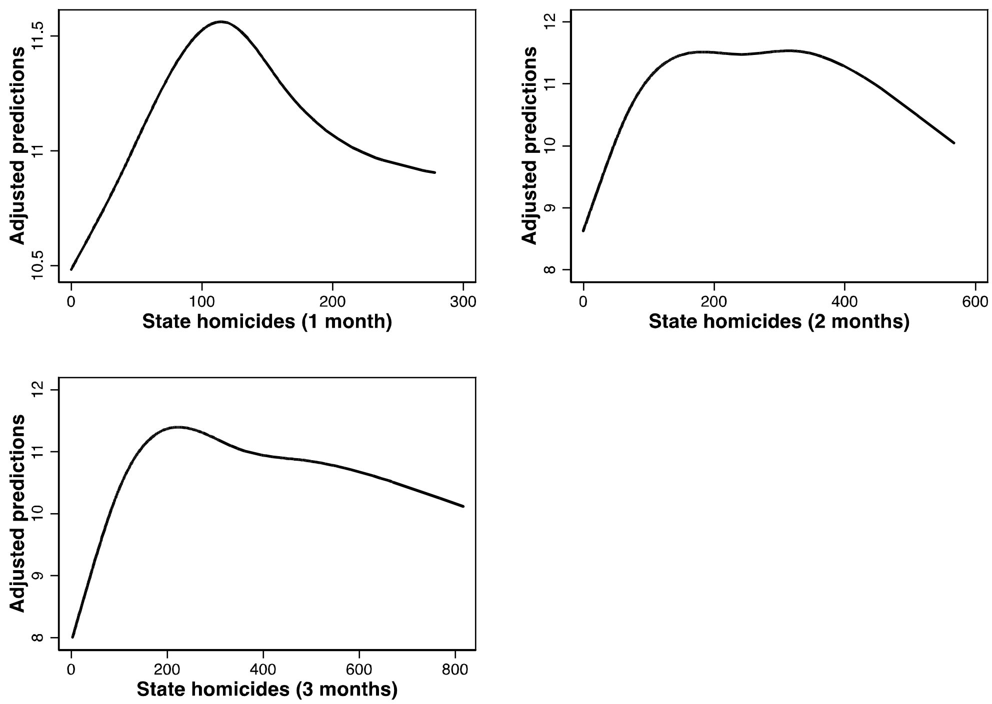
NOTE: Results presented are coefficients with standard errors clustered at the municipal- and state-level in parentheses, depending on the analysis. All the models include municipality by wave, calendar year, and month fixed-effects and control for the individual and household controls in Table 1.1.
*** p<0.01, **p<0.05, *p<0.10 (two-tailed tests).

Figure A.1 Predicted Cognitive Scores as a Function of Municipal Homicides using Restricted Cubic Splines



NOTE: Knots at 10, 50, 90, 95, and 99 percentiles.

Figure A.2 Predicted Cognitive Scores as a Function of State Homicides using Restricted Cubic Splines



NOTE: Knots at 10, 50, 90, 95, and 99 percentiles.

Table A.4 Fixed-Effects Models of Municipal and State Homicides Predicting Cognitive Scores (with average cognitive scores of everyone in the household above 12 years old as a control)

Homicides	Municipal			State		
	(1)	(2)	(3)	(1)	(2)	(3)
t - 1	0.024			0.011*		
	(0.023)			(0.006)		
t - 1 (sq)	-0.0004**			-0.00004*		
	(0.0002)			(0.00002)		
t - (1 + 2)		0.028**			0.014**	
		(0.013)			(0.005)	
t - (1 + 2) (sq)		-0.0002***			-0.00002**	
		(0.00006)			(0.000009)	
t - (1 + 2 + 3)			0.023***			0.008***
			(0.009)			(0.002)
t - (1 + 2 + 3) (sq)			-0.00008***			-0.00001***
			(0.00002)			(0.000003)
P-value for U-test	0.148	0.013	0.005	0.041	0.018	0.004
P-value for F-test	0.000	0.010	0.005	0.149	0.057	0.013
R^2	0.34	0.34	0.35	0.34	0.35	0.35
N	14,871	14,871	14,871	14,871	14,871	14,871

NOTE: Results presented are coefficients with standard errors clustered at the municipal- and state-level in parentheses, depending on the analysis. All the models include municipality by wave, calendar year, and month fixed-effects and control for the individual and household controls in Table 1.1.
*** p<0.01, **p<0.05, *p<0.10 (two-tailed tests).

Table A.5 Fixed-Effects Models of Municipal and State Homicides Predicting Cognitive Scores (with lagged cognitive scores as a control)

Homicides	Municipal			State		
	(1)	(2)	(3)	(1)	(2)	(3)
t - 1	0.065			0.015		
	(0.040)			(0.011)		
t - 1 (sq)	-0.0009***			-0.00008**		
	(0.0003)			(0.00003)		
t - (1 + 2)		0.049**			0.018***	
		(0.023)			(0.006)	
t - (1 + 2) (sq)		-0.0003***			-0.00004***	
		(0.0001)			(0.00001)	
t - (1 + 2 + 3)			0.027**			0.012**
			(0.012)			(0.004)
t - (1 + 2 + 3) (sq)			-0.0001***			-0.00002***
			(0.00003)			(0.000005)
P-value for U-test	0.051	0.019	0.012	0.102	0.007	0.007
P-value for F-test	0.000	0.000	0.000	0.014	0.029	0.015
R^2	0.27	0.27	0.27	0.27	0.27	0.27
N	4,850	4,850	4,850	4,850	4,850	4,850

NOTE: Results presented are coefficients with standard errors clustered at the municipal- and state-level in parentheses, depending on the analysis. All the models include municipality by wave, calendar year, and month fixed-effects and control for the individual and household controls in Table 1.1.
*** p<0.01, **p<0.05, *p<0.10 (two-tailed tests).

Table A.6 Fixed-Effects Models of Municipal and State Homicides Predicting Cognitive Scores (without individual- and household-level controls)

Homicides	Municipal			State		
	(1)	(2)	(3)	(1)	(2)	(3)
t - 1	0.045			0.014		
	(0.034)			(0.009)		
t - 1 (sq)	-0.00066**			-0.00006*		
	(0.0003)			(0.00003)		
t - (1 + 2)		0.032*			0.015**	
		(0.017)			(0.006)	
t - (1 + 2) (sq)		-0.0002**			-0.00003**	
		(0.00008)			(0.00001)	
t - (1 + 2 + 3)			0.024**			0.009**
			(0.010)			(0.004)
t - (1 + 2 + 3) (sq)			-0.00008***			-0.00001***
			(0.00003)			(0.000004)
P-value for U-test	0.095	0.028	0.010	0.056	0.012	0.008
P-value for F-test	0.000	0.004	0.014	0.114	0.041	0.018
R^2	0.13	0.13	0.13	0.13	0.14	0.14
N	16,552	16,552	16,552	16,552	16,552	16,552

NOTE: Results presented are coefficients with standard errors clustered at the municipal- and state-level in parentheses, depending on the analysis. All the models include municipality by wave, calendar year, and month fixed-effects.
*** p<0.01, **p<0.05, *p<0.10 (two-tailed tests).

Table A.7 Fixed-Effects Models of Municipal and State Homicides Predicting Normalized Cognitive Scores (by age and wave, including children and teenagers 18-year-old and younger)

Homicides	Municipal			State		
	(1)	(2)	(3)	(1)	(2)	(3)
t - 1	0.002			0.0009**		
	(0.001)			(0.0004)		
t - 1 (sq)	-0.00003***			-0.000003**		
	(0.00001)			(0.000001)		
t - (1 + 2)		0.001*			0.0009***	
		(0.0007)			(0.0003)	
t - (1 + 2) (sq)		-0.00001***			-0.000002***	
		(0.000003)			(0.0000005)	
t - (1 + 2 + 3)			0.001**			0.0005***
			(0.0004)			(0.0001)
t - (1 + 2 + 3) (sq)			-0.000004***			-0.0000006***
			(0.000001)			(0.0000002)
P-value for U-test	0.069	0.026	0.010	0.022	0.005	0.002
P-value for F-test	0.000	0.000	0.001	0.097	0.021	0.007
R^2	0.17	0.17	0.17	0.17	0.17	0.17
N	18,454	18,454	18,454	18,454	18,454	18,454

NOTE: Results presented are coefficients with standard errors clustered at the municipal- and state-level in parentheses, depending on the analysis. All the models include municipality by wave, calendar year, and month fixed-effects and control for the individual and household controls in Table 1.1 and an indicator variable for type of test administered.
*** p<0.01, **p<0.05, *p<0.10 (two-tailed tests).

Table A.8 Fixed-Effects Models of Municipal and State Homicide Rates Predicting Cognitive Scores

Homicide rates	Municipal			State		
	(1)	(2)	(3)	(1)	(2)	(3)
t - 1	-4.971			30.326		
	(6.641)			(24.356)		
t - 1 (sq)	6.951			-336.033		
	(45.010)			(205.172)		
t - 2		4.945			70.678**	
		(4.309)			(25.592)	
t - 2 (sq)		-22.888			-575.491**	
		(16.129)			(240.115)	
t - 3			8.434**			24.931*
			(3.859)			(13.837)
t - 3 (sq)			-33.315**			-236.917***
			(15.204)			(59.658)
P-value for U-test	1.000	0.126	0.026	0.114	0.120	0.043
P-value for F-test	0.489	0.364	0.073	0.200	0.039	0.000
R^2	0.31	0.31	0.31	0.31	0.31	0.31
N	16,019	16,019	16,019	16,021	16,021	16,021

NOTE: Results presented are coefficients with standard errors clustered at the municipal- and state-level in parentheses, depending on the analysis. All the models include municipality by wave, calendar year, and month fixed-effects and control for the individual and household controls in Table 1.1.
*** p<0.01, **p<0.05, *p<0.10 (two-tailed tests).

Table A.9 Fixed-Effects Models of Municipal and State Homicides Predicting Cognitive Scores (with municipality population as control)

Homicides	Municipal			State		
	(1)	(2)	(3)	(1)	(2)	(3)
t - 1	0.038			0.017**		
	(0.025)			(0.006)		
t - 1 (sq)	-0.00057**			-0.00006***		
	(0.0002)			(0.00002)		
t - (1 + 2)		0.029**			0.017***	
		(0.015)			(0.005)	
t - (1 + 2) (sq)		-0.0002***			-0.00003***	
		(0.00007)			(0.00001)	
t - (1 + 2 + 3)			0.022**			0.010***
			(0.009)			(0.003)
t - (1 + 2 + 3) (sq)			-0.00007***			-0.00001***
			(0.00003)			(0.000003)
P-value for U-test	0.061	0.024	0.010	0.007	0.004	0.001
P-value for F-test	0.000	0.007	0.007	0.030	0.011	0.004
R^2	0.31	0.31	0.31	0.31	0.31	0.31
N	16,019	16,019	16,019	16,019	16,019	16,019

NOTE: Results presented are coefficients with standard errors clustered at the municipal- and state-level in parentheses, depending on the analysis. All the models include municipality by wave, calendar year, and month fixed-effects and control for the individual and household controls in Table 1.1.
*** p<0.01, **p<0.05, *p<0.10 (two-tailed tests).

Table A.10 Fixed-Effects Models of Cognitive Scores Predicting Timing of Test

Variable	(1)	(2)	(3)	(4)
Cognitive score	-0.004	-0.005	0.006	-0.006
	(0.010)	(0.012)	(0.010)	(0.014)
Age		0.019		0.022
		(0.023)		(0.024)
Gender (male)		-0.029		-0.023
		(0.052)		(0.053)
Education (none or pre-k)				
Education (elementary)		-0.110		-0.150
		(0.130)		(0.108)
Education (secondary)		0.362		0.351
		(0.256)		(0.242)
Attends school		-0.126		-0.137
		(0.338)		(0.453)
Ever attended school		0.523		0.523
		(0.370)		(0.475)
Repeated grade		0.139		0.116
		(0.098)		(0.097)
Indigenous		-0.080		-0.093
		(0.169)		(0.175)
Accident		0.689**		0.521
		(0.322)		(0.456)
Sickness		0.032		0.052***
		(0.020)		(0.017)
Floors		-0.218		-0.073
		(0.142)		(0.147)
Sewage		0.358*		0.578**
		(0.212)		(0.224)
Toilet		-0.195		-0.148
		(0.150)		(0.189)
Electricity		-1.265***		-1.341**
		(0.425)		(0.616)
Indigenous household		-0.045		-0.207
		(0.128)		(0.166)

Table A.10 (Continued)

Female headed		0.180		0.226
		(0.115)		(0.132)
Adults middle school		0.091		0.150
		(0.099)		(0.113)
Adults minimum wage		-0.152		-0.036
		(0.110)		(0.110)
2 people per room		0.073		0.177
		(0.087)		(0.114)
Children		0.028		0.088**
		(0.041)		(0.037)
Household US migration		-0.239**		-0.450***
		(0.093)		(0.124)
Municipality change		5.429***		2.740**
		(1.191)		(1.152)
Crime victimization		0.083		-0.199
		(0.408)		(0.533)
Shocks		-0.033		-0.163
		(0.111)		(0.105)
Municipality by wave fixed-effects	Yes	Yes	No	No
State by wave fixed-effects	No	No	Yes	Yes
R^2	0.24	0.26	0.21	0.23
N	16,550	16,019	16,597	16,065

NOTE: Results presented are coefficients with standard errors clustered at the municipal- and state-level in parentheses, depending on the analysis (municipality by wave or state by wave fixed-effects).
*** p<0.01, **p<0.05, *p<0.10 (two-tailed tests).

Table A.11 Fixed-Effects Models of Future Municipal and State Homicides Predicting Cognitive Scores

Homicides	Municipal			State		
	(1)	(2)	(3)	(1)	(2)	(3)
t + 1	0.011			0.013		
	(0.022)			(0.008)		
t + 1 (sq)	-0.0001			-0.00005*		
	(0.0002)			(0.00003)		
t + (1 + 2)		0.014			0.006	
		(0.016)			(0.005)	
t + (1 + 2) (sq)		-0.0001			-0.00001	
		(0.0001)			(0.000008)	
t + (1 + 2 + 3)			0.004			0.003
			(0.014)			(0.003)
t + (1 + 2 + 3) (sq)			-0.00001			-0.000006
			(0.00004)			(0.000003)
P-value for U-test	0.308	0.193	0.399	0.072	0.111	0.173
P-value for F-test	0.155	0.036	0.691	0.030	0.009	0.002
N	16,021	16,021	16,021	16,021	16,021	16,021

NOTE: Results presented are coefficients with standard errors clustered at the municipal- and state-level in parentheses, depending on the analysis. All the models include municipality by wave, calendar year, and month fixed-effects and control for the individual and household controls in Table 1.1.
*** p<0.01, **p<0.05, *p<0.10 (two-tailed tests).

Table A.12 Fixed-Effects Models of Municipal Homicides Predicting Cognitive Scores (restricted to children tested within 6 and 12 months of initial month of testing).

Municipal homicides	6 months			12 months		
	(1)	(2)	(3)	(1)	(2)	(3)
t - 1	0.040			0.033		
	(0.033)			(0.030)		
t - 1 (sq)	-0.0007***			-0.0005**		
	(0.0003)			(0.0002)		
t - (1 + 2)		0.052*			0.034	
		(0.027)			(0.021)	
t - (1 + 2) (sq)		-0.0003***			-0.0002**	
		(0.0001)			(0.00008)	
t - (1 + 2 + 3)			0.031*			0.029**
			(0.017)			(0.013)
t - (1 + 2 + 3) (sq)			-0.0001***			-0.00009***
			(0.00004)			(0.00003)
P-value for U-test	0.111	0.031	0.033	0.134	0.050	0.012
P-value for F-test	0.000	0.000	0.000	0.000	0.000	0.002
R^2	0.31	0.31	0.31	0.31	0.31	0.31
N	14,093	14,093	14,093	15,371	15,371	15,371

NOTE: Results presented are coefficients with standard errors clustered at the municipal level in parentheses. All the models include municipality by wave, calendar year, and month fixed-effects and control for the individual and household controls in Table 1.1.
*** p<0.01, **p<0.05, *p<0.10 (two-tailed tests).

Table A.13 Fixed-Effects Models of State Homicides Predicting Cognitive Scores (restricted to children tested within 6 and 12 months of initial month of testing).

State homicides	6 months			12 months		
	(1)	(2)	(3)	(1)	(2)	(3)
t - 1	0.021			0.020*		
	(0.015)			(0.010)		
t - 1 (sq)	-0.00009*			-0.00008**		
	(0.00005)			(0.00003)		
t - (1 + 2)		0.026***			0.021***	
		(0.009)			(0.005)	
t - (1 + 2) (sq)		-0.00005***			-0.00004***	
		(0.00001)			(0.00001)	
t - (1 + 2 + 3)			0.024***			0.017***
			(0.007)			(0.004)
t - (1 + 2 + 3) (sq)			-0.00003***			-0.00002***
			(0.00001)			(0.000004)
P-value for U-test	0.097	0.003	0.001	0.028	0.000	0.000
P-value for F-test	0.006	0.000	0.000	0.008	0.001	0.000
R^2	0.31	0.32	0.32	0.31	0.31	0.31
N	14,093	14,093	14,093	15,371	15,371	15,371

NOTE: Results presented are coefficients with standard errors clustered at the state level in parentheses. All the models include municipality by wave, calendar year, and month fixed-effects and control for the individual and household controls in Table 1.1.
*** p<0.01, **p<0.05, *p<0.10 (two-tailed tests).

Table A.14 Fixed-Effects Linear Probability Models of Municipality Migration with Homicides as Predictor

Municipality change	Without controls		With controls	
	(1)	(2)	(3)	(4)
t - 1 year	0.0095		0.0107	
	(0.009)		(0.011)	
t - 2 years		0.0056		0.0063
		(0.006)		(0.007)
R^2	0.90	0.90	0.90	0.90
N	44,443	44,443	42,337	42,337

NOTE: Results presented are coefficients with standard errors clustered at the municipal level in parentheses. All the models include individual, municipality-by-wave, calendar year and month, and community type fixed-effects. Models with additional controls also include the individual and household variables in Table 2.1, as well as the natural log of the municipality population.
*** p<0.01, **p<0.05, *p<0.10 (two-tailed tests).

Table A.15 Fixed-Effects Models of Weight-related Outcomes with Future Homicides as Predictor

Homicides	Body Mass Index		Waist Circumference	
	(1)	(2)	(3)	(4)
t + 1 year	-0.001		-0.002	
	(0.003)		(0.005)	
t + 2 years		-0.001		-0.002
		(0.002)		(0.002)
N	36,957	36,957	37,341	37,341

NOTE: Results presented are coefficients with standard errors clustered at the municipal level in parentheses. All the models include individual, municipality-by-wave, calendar year and month, and community type fixed-effects and control for the individual and household controls in Table 2.1, as well as the natural log of the municipality population.
*** p<0.01, **p<0.05, *p<0.10 (two-tailed tests).

Table A.16 Fixed-Effects Linear Probability Models of Attrition with Homicides as Predictor

Homicides	BMI sample		WC sample	
	(1)	(2)	(3)	(4)
t - 1 year	-0.0168*		-0.0071	
	(0.010)		(0.011)	
t - 2 years		-0.0075		0.00004
		(0.007)		(0.007)
R^2	0.78	0.78	0.79	0.79
N	44,517	44,517	44,517	44,517

NOTE: Results presented are coefficients with standard errors clustered at the municipal level in parentheses. All the models include individual, municipality-by-wave, calendar year and month, and community type fixed-effects.
*** p<0.01, **p<0.05, *p<0.10 (two-tailed tests).

Table A.17 Fixed-Effects Models of Weight-related Outcomes with Homicides, Sugary and Alcoholic Drinks Consumption, and Physical Activity Variables as Predictors

Homicides	Body Mass Index		Waist Circumference	
	(1)	(2)	(3)	(4)
t - 1 year	0.0036***		0.0037**	
	(0.001)		(0.0018)	
t - 2 years		0.0024***		0.0029**
		(0.0007)		(0.001)
Soft drinks	0.109*	0.109*	0.303*	0.302*
	(0.059)	(0.059)	(0.169)	(0.169)
Alcohol	0.181***	0.181***	0.606***	0.606***
	(0.056)	(0.056)	(0.155)	(0.155)
Exercise	-0.0014***	-0.0014***	-0.0023**	-0.0023**
	(0.0004)	(0.0004)	(0.001)	(0.001)
Screen time	0.007**	0.007**	0.018**	0.018**
	(0.003)	(0.003)	(0.007)	(0.007)
R^2	0.89	0.89	0.86	0.86
N	34,286	34,286	34,661	34,661

NOTE: Results presented are coefficients with standard errors clustered at the municipal level in parentheses. All the models include individual, municipality-by-wave, calendar year and month, and community type fixed-effects and control for the individual and household controls in Table 2.1, as well as the natural log of the municipality population.
*** p<0.01, **p<0.05, *p<0.10 (two-tailed tests).

Table A.18 Fixed-Effects Models of Weight-related Outcomes with Homicides as Predictor (excluding observations of individuals with BMI≤18.5)

Homicides	Body Mass Index		Waist Circumference	
	(1)	(2)	(3)	(4)
t - 1 year	0.0032***		0.0039**	
	(0.001)		(0.0017)	
t - 2 years		0.0022***		0.0031**
		(0.0007)		(0.001)
R^2	0.89	0.89	0.86	0.86
N	36,042	36,042	36,459	36,459

NOTE: Results presented are coefficients with standard errors clustered at the municipal level in parentheses. All the models include individual, municipality-by-wave, calendar year and month, and community type fixed-effects and control for the individual and household controls in Table 2.1, as well as the natural log of the municipality population.
*** p<0.01, **p<0.05, *p<0.10 (two-tailed tests).

Table A.19 Fixed-Effects Models of Weight-related Outcomes with Homicides as Predictor (excluding observations of individuals with BMI≤18.5)

Homicides	Body Mass Index		Waist Circumference	
	(1)	(2)	(3)	(4)
t - 1 year	0.0035***		0.0036**	
	(0.001)		(0.0016)	
t - 2 years		0.0024***		0.0031**
		(0.0006)		(0.001)
Pregnancy / lactation	0.448***	0.450***	0.924*	0.926*
	(0.123)	(0.123)	(0.538)	(0.538)
R^2	0.88	0.88	0.86	0.86
N	38,521	38,521	38,079	38,079

NOTE: Results presented are coefficients with standard errors clustered at the municipal level in parentheses. All the models include individual, municipality-by-wave, calendar year and month, and community type fixed-effects and control for the individual and household controls in Table 2.1, as well as the natural log of the municipality population. *** p<0.01, **p<0.05, *p<0.10 (two-tailed tests).

3

Fear of crime, armed conflict, and collective efficacy in Mexico

Table A.20 Results of Fixed-Effects Models Predicting Fear of Crime Including all the Communities (96 Communities)

Variable	Model 1	Model 2	Model 3	Model 4
Municipal homicide rate	0.00547***		0.00707	
	(0.00107)		(0.00440)	
State homicide rate		0.00883***		0.0282***
		(0.00178)		(0.00850)
Military and organized armed groups	1.854**	1.893**	8.010***	6.775**
	(0.584)	(0.589)	(2.154)	(2.089)
Collective efficacy X Municipal homicide rate			-0.00138	
			(0.00452)	
Collective efficacy X State homicide rate				-0.0182*
				(0.00778)
Collective efficacy X Military and organized armed groups			-7.470*	-6.154**
			(2.418)	(2.344)
Collective efficacy	-0.000531	0.0158	-0.107	0.211
	-0.115	-0.115	-0.147	-0.187
Constant	-0.833	-0.355	-0.647	-0.322
	(1.402)	(1.412)	(1.428)	(1.433)
R-squared	0.044	0.044	0.045	0.046
N (individuals X waves)	14,958	14,958	14,958	14,958

Table A.20 (Continued)

NOTE: Results presented are coefficients with standard errors clustered at the individual level in parentheses. All the models control for the individual, household and community controls in Table 3.1.
*** $p<0.001$, **$p<0.01$, *$p<0.05$ (two-tailed tests).

Table A.21 Results of Fixed-Effects Models Predicting Fear of Crime Including Communities with at least 30 Households (85 Communities)

Variable	Model 1	Model 2	Model 3	Model 4
Municipal homicide rate	0.00631***		0.00876*	
	(0.00111)		(0.00441)	
State homicide rate		0.0102***		0.0340***
		(0.00176)		(0.00827)
Military and organized armed groups	2.018***	2.085***	7.631***	5.899**
	(0.613)	(0.616)	(2.204)	(2.124)
Collective efficacy X Municipal homicide rate			-0.00234	
			(0.00468)	
Collective efficacy X State homicide rate				-0.0235**
				(0.00798)
Collective efficacy X Military and organized armed groups			-7.187**	-5.172*
			(2.586)	(2.506)
Collective efficacy	-0.0210	-0.00296	-0.0777	0.319
	(0.115)	(0.116)	(0.145)	(0.190)
Constant	-2.113	-1.832	-1.874	-1.958
	(1.403)	(1.410)	(1.443)	(1.434)
R-squared	0.047	0.048	0.049	0.050
N (individuals X waves)	14,610	14,610	14,610	14,610

NOTE: Results presented are coefficients with standard errors clustered at the individual level in parentheses. All the models control for the individual, household and community controls in Table 3.1.
*** p<0.001, **p<0.01, *p<0.05 (two-tailed tests).

Table A.22 Results of Fixed-Effects Models Predicting Fear of Crime with Multiple Imputation

Variable	Model 1	Model 2	Model 3	Model 4
Municipal homicide rate	0.0061***		0.0054	
	(0.0011)		(0.0041)	
State homicide rate		0.0098***		0.0257**
		(0.0017)		(0.0077)
Military and organized armed groups	1.7583**	1.8200**	1.9863***	1.4649**
	(0.5724)	(0.5744)	(0.5650)	(0.5438)
Collective efficacy X Municipal homicide rate			0.0001	
			(0.0004)	
Collective efficacy X State homicide rate				-0.0015*
				(0.0008)
Collective efficacy X Military and organized armed groups			-0.2032**	-0.1408*
			(0.0685)	(0.0663)
Collective efficacy	-0.0452	-0.0309	0.0114	0.0347*
	(0.1090)	(0.1093)	(0.0127)	(0.0162)
Constant	-1.3359	-1.0735	-1.0670	-1.0931
	(1.3281)	(1.3359)	(1.3539)	(1.3479)
N (individuals X waves)	17,030	17,030	17,030	17,030

NOTE: Results presented are coefficients with standard errors clustered at the individual level in parentheses. All the models control for the individual, household and community controls in Table 3.1.
*** p<0.001, **p<0.01, *p<0.05 (two-tailed tests).

Table A.23 Results of Random-Effects Models Predicting Fear of Crime

Variable	Model 1	Model 2	Model 3	Model 4
Municipal homicide rate	0.00291** (0.00087)		0.00788* (0.00308)	
State homicide rate		0.00442*** (0.00125)		0.0197*** (0.00508)
Military and organized armed groups	1.477** (0.438)	1.455** (0.443)	6.598*** (1.408)	5.552*** (1.384)
Collective efficacy X Municipal homicide rate			-0.0048 (0.00322)	
Collective efficacy X State homicide rate				-0.0152** (0.0049)
Collective efficacy X Military and organized armed groups			-6.098*** (1.5884)	-4.979** (1.5431)
Collective efficacy	-0.01949 (0.0693)	-0.02341 (0.0692)	0.0215 (0.0826)	0.1716 (0.0994)
Constant	1.004 (0.613)	1.338 (0.616)	0.981 (0.626)	1.265* (0.626)
R-squared	0.064	0.065	0.066	0.067
N (individuals X waves)	14,818	14,818	14,818	14,818

NOTE: Results presented are coefficients with standard errors clustered at the individual level in parentheses. All the models control for the individual, household and community controls in Table 3.1.
*** p<0.001, **p<0.01, *p<0.05 (two-tailed tests).

Table A.24 Results of Fixed-Effects Models Predicting Fear of Crime with Standard Errors Clustered at the Community Level

Variable	Model 1	Model 2	Model 3	Model 4
Municipal homicide rate	0.00608**		0.00828	
	(0.00185)		(0.00568)	
State homicide rate		0.00983***		0.0331**
		(0.00262)		(0.00970)
Military and organized armed groups	1.922*	1.983*	7.462**	5.705*
	(0.924)	(0.952)	(2.573)	(2.186)
Collective efficacy X Municipal homicide rate			-0.00208	
			(0.00669)	
Collective efficacy X State homicide rate				-0.0230*
				(0.00955)
Collective efficacy X Military and organized armed groups			-7.081*	-5.062*
			(2.988)	(2.352)
Collective efficacy	-0.0273	-0.0100	-0.0882	0.300
	(0.251)	(0.264)	(0.249)	(0.292)
Constant	-2.074	-1.797	-1.844	-1.937
	(1.993)	(1.999)	(1.970)	(1.933)
R-squared	0.047	0.047	0.049	0.050
N (individuals X waves)	14,818	14,818	14,818	14,818

NOTE: Results presented are coefficients with standard errors clustered at the community level in parentheses. All the models control for the individual, household and community controls in Table 3.1.
*** p<0.001, **p<0.01, *p<0.05 (two-tailed tests).

Table A.25 Results of Fixed-Effects Models Predicting Fear of Crime using Community Averages for the MOAG and Collective Efficacy

Variable	Model 1	Model 2	Model 3	Model 4
Municipal homicide rate	0.00610***		0.00678	
	(0.00110)		(0.00436)	
State homicide rate		0.00985***		0.0301***
		(0.00175)		(0.00822)
Military and organized armed groups	0.493**	0.512**	2.192***	1.616**
	(0.172)	(0.173)	(0.607)	(0.585)
Collective efficacy X Municipal homicide rate			-1.25e-05	
			(0.000472)	
Collective efficacy X State homicide rate				-0.00197*
				(0.000807)
Collective efficacy X Military and organized armed groups			-0.224**	-0.155*
			(0.0728)	(0.0708)
Collective efficacy	-0.00435	-0.00286	0.0169	0.0447**
	(0.0112)	(0.0112)	(0.0133)	(0.0169)
Constant	-1.944	-1.662	-1.832	-1.919
	(1.401)	(1.408)	(1.432)	(1.424)
R-squared	0.047	0.047	0.049	0.050
N (individuals X waves)	14,818	14,818	14,818	14,818

NOTE: Results presented are coefficients with standard errors clustered at the individual level in parentheses. All the models control for the individual, household and community controls in Table 3.1.
*** p<0.001, **p<0.01, *p<0.05 (two-tailed tests).

Table A.26 Results of Fixed-Effects Models Predicting Fear of Crime with Community Averages Disregarding Household Perception

Variable	Model 1	Model 2	Model 3	Model 4
Municipal homicide rate	0.00616*** (0.00110)		0.0113 (0.0155)	
State homicide rate		0.00998*** (0.00174)		0.0824** (0.0270)
Military and organized armed groups	0.505** (0.169)	0.529** (0.170)	6.792** (2.379)	4.708* (2.302)
Collective efficacy X Municipal homicide rate			-0.000145 (0.000477)	
Collective efficacy X State homicide rate				-0.00216** (0.000808)
Collective efficacy X Military and organized armed groups			-0.203** (0.0756)	-0.137 (0.0734)
Collective efficacy	-0.00409 (0.0110)	-0.00249 (0.0110)	0.0172 (0.0132)	0.0465** (0.0168)
Constant	-1.837 (1.410)	-1.581 (1.415)	-2.221 (1.456)	-2.980* (1.481)
R-squared	0.047	0.047	0.048	0.050
N (individuals X waves)	14,818	14,818	14,818	14,818

NOTE: Results presented are coefficients with standard errors clustered at the individual level in parentheses. All the models control for the individual, household and community controls in Table 3.1.
*** p<0.001, **p<0.01, *p<0.05 (two-tailed tests).

Table A.27 Results of Treatment Selection Tests

Variable	Homicide rate (municipality)	Homicide rate (state)	Military and organized armed groups (community)	Military and organized armed groups (household)
Fear of crime (wave 2)	-0.417	-0.00129	0.000441	-0.000487
	(0.252)	(0.183)	(0.000619)	(0.00601)
Fear of crime (wave 1 + wave 2)	-0.548**	-0.600***	0.000237	0.00520
	(0.163)	(0.116)	(0.000374)	(0.00391)
Constant	19.17***	19.98***	-0.00182*	0.168***
	(0.368)	(0.277)	(0.000758)	(0.00735)
R-squared	0.006	0.007	0.001	0.001
N	6,585	6,585	6,585	6,317

NOTE: Results presented are coefficients with standard errors clustered at the individual level in parentheses.
*** p<0.001, **p<0.01, *p<0.05 (two-tailed tests).

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