Impact of Violent Crime on Risk Aversion: Evidence from the Mexican Drug War

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Abstract

Whereas attitudes towards risk are thought to play an important role in many decisions over the life-course, factors that affect those attitudes are not fully understood. Using longitudinal survey data collected in Mexico before and during the Mexican war on drugs, we investigate how an individual's risk attitudes change with variation in levels of insecurity and uncertainty brought on by unprecedented changes in local-area violent crime due to the war on drugs. Exploiting the fact that the timing, virulence and spatial distribution of changes in violent crime were unanticipated, we establish the changes can plausibly be treated as exogenous in models that also take into account unobserved characteristics of individuals that are fixed over time. As local-area violent crime increases, there is a rise in risk aversion that is distributed through the entire local population.

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I. Introduction

Attitudes people have towards risk influence key choices over the life course and are thought to play an important role in determining the evolution of individual social and economic status, health and wellbeing. Studies have established that willingness to take risks is associated with decisions made under uncertainty including insurance acquisition, precautionary saving decisions, investment behavior, occupational choice, technology adoption and geographic mobility (Barsky et al., 1997; Bellemare and Shearer, 2010; Bryan, Chowdhury and Mobarak, 2014; Charles and Hurst, 2003; Deaton, 1991; Dupas, 2014; Kan, 2003; Kimball et al., 2008; Lusardi, 1998).

There is less agreement in the literature on the extent to which attitudes towards risk are stable over the life course. Implicit in many economic models is the assumption that an individual's risk attitudes are immutable whereas research in psychology and the health sciences typically assumes these attitudes react to changes in an individual's circumstances (Carmil and Breznitz, 1991; Tedeschi and Calhoun, 2004). Several recent studies in economics have empirically examined whether measured risk attitudes are responsive to major changes in an individual's environment, including earthquakes, floods, tsunamis, financial crisis, and outbreaks of violent conflict (Callen et al., 2014; Cameron and Shah, 2013; Cassar et al., 2011; Guiso et al. 2013; Ingwersen et al., 2016; Hanaoka et al., 2015; Jakiela and Ozier, 2016; Malmendier and Nagel, 2011; Moya, 2017; Voors et al., 2012).

Separating selection from causal mechanisms is a major challenge in this literature since exposure to drivers that are thought to affect risk attitudes are potentially correlated with pre-existing characteristics. For example, relatively more risk averse individuals likely engage in behaviors that mitigate exposure to uncertainty in the environment, which will result in sorting of individuals by exposure, and thus contaminate interpretation of observed associations between exposure to uncertainty and risk attitudes. To address this concern, investigators have examined the link between risk attitudes and exposure to local area shocks, such as floods, earthquakes or political violence. Not all such events though are, in fact, shocks and it is critically important to establish that selective geographic sorting because of the perceived risks of the event does not contaminate causal inference. Empirical studies have primarily relied on cross-section surveys and so are not able to take into account behavioral responses to the event such as migration away from the area.

This study directly addresses these challenges. Using longitudinal survey data that elicits risk attitudes from the same respondents before and after the onset of the Mexican war on drugs, we exploit plausibly exogenous variation in the timing, location, and magnitude of the rise in violent crime to identify its effect

on risk. Key assumptions necessary to give these estimates a causal interpretation are tested drawing on the panel dimension of the survey.

It is well documented that the outbreak of violence in Mexico had political origins. One of the main causes was a fundamental change in the strategy of the Mexican government towards combating drug trafficking organizations when Calderon took over the presidency in December 2006. After some brief initial success, an unanticipated and unprecedented rise in crime quickly followed. This surge in violent crime diffused widely throughout the country, affecting many regions that had previously had no exposure to the war on drugs and creating geographic heterogeneity that was uncorrelated with previous trends in local demographic, economic, security, and infrastructure characteristics (Brown, 2016; Velasquez, 2015). Our identification strategy exploits both the temporal and geographic variation of this rise in violence across Mexico.

Given the magnitude of the outbreak of violent crime, the increasing brutality of the crimes, and the heightened visibility of the violence due to press coverage and active promotion by drug cartels through narco-messages, the psychological exposure to this change in the environment is likely salient to most of the population living in affected localities[1]. When considering this type of widespread environmental shock, there are several potential mechanisms through which it may have an impact on risk attitudes. First, exposure to violence has the potential to change an individual's perception of the riskiness of the current/future environment or their tolerance for additional risk. Second, the increase in potential victimization is likely to provoke heightened anxiety and fear, which has been shown to induce increased risk averse decision-making (Lerner and Keltner, 2001; Raghunathan and Pham, 1999). Third, given the evidence that risk aversion is negatively associated with income and wealth (Barsky et al., 1997; Guiso and Paiella, 2008), another potential link between crime and risk preferences is through the negative effect that the Mexican drug war has had on the economic outcomes of the affected population (Dell, 2015; Robles et al., 2013, Velásquez, 2015).

To explore whether changes in the level of violence affected risk attitudes of those in the affected localities, we use data from the Mexican Family Life Survey (MxFLS), which is ideally suited for this research. The MxFLS is representative of the Mexican population living in Mexico in 2002, when the baseline survey was conducted. Subsequently, two additional follow-ups were conducted, in which respondents' attitudes towards risk were elicited by asking individual respondents in face-to-face interviews to choose between

[1] The term "drug cartel" refers to organized crime organizations involved in drug-trafficking. It does not imply any collusion to set prices. We use indistinctively the terms "drug cartel", OCG and traffickers' organizations.

gambles with different payoffs[2]. Key for our study, the first follow-up (MxFLS2) took place during a time of relatively stable levels of violent crime and the second follow-up (MxFLS3) was conducted after the major escalation in violence. The individual level information from MxFLS is combined with municipality- and month-specific homicide data collected by the National Institute of Statistics and Geography (INEGI) in order to measure how attitudes towards risk vary as the level of local area violent crime changes over time. The relationship between the timing of the escalation in violence and the dates of survey interviews is displayed in Figure 1, which plots the monthly national homicide rate per 10,000 inhabitants from 2000 to 2011 and highlights months in which interviews that collected information about risk attitudes were conducted in MxFLS2 and MxFLS3. The longitudinal dimension of MxFLS is exploited to provide empirical evidence on the likely validity of threats to identifying assumptions necessary to interpret our estimates as causal. This paper advances the literature linking risk attitudes and environmental shocks by combining high quality longitudinal survey data with administrative information on homicides that span a period of diverse geographic and sharp temporal variation in violent crime in Mexico. There are several advantages of our research design.

First, we examine changes in risk attitudes before and after the onset of the Mexican war on drugs for the same individuals interviewed in a population-representative survey. Moreover, all individual-specific characteristics of respondents that are fixed over time are taken into account in the estimation through the inclusion of individual fixed effects. This is a significant advance over the existing literature.

Second, residential sorting related to a locale's level of safety may be correlated with individual characteristics and lead to a spurious correlation between exposure to violence and risk attitudes. While one way to address this issue is to use an environmental shock thought to be plausibly exogenous, we demonstrate that even in the context of an unanticipated event, if a cross-sectional approach is used, this potential confound can still significantly impact one's conclusions. To demonstrate this we compare results from an analysis using only cross-sectional data from before the recent surge in violence, an analysis only using cross-sectional data from after the plausibly exogenous escalation in violence, and an analysis that combines these two time periods and adds individual fixed effects. We find that when utilizing only historical variation in violence levels or only current levels caused by a plausible exogenous event it

[2] Even though the literature generally considers these empirical measures of risk aversion as capturing underlying risk preferences, we would like to be cautious about this interpretation. In economic theory, risk preferences are summarized by measures derived from utility-based models of behavior under uncertainty. These models require making assumptions on a number of issues (such as the form of the utility function, whether the amounts of the gambles are integrated with personal wealth, whether savings are allowed and whether background risk is accounted for (Arrow, 1970; Pratt, 1964; Gollier, 2000)). We remain skeptical regarding these assumptions and to avoid confusion, we do not interpret our empirical measures of risk aversion as capturing underlying preferences, but rather more generally as capturing attitudes towards risk.

appears that exposure to violence is related to decreased risk aversion or is unrelated to risk attitudes, respectively.[3]

However, after taking into account unobserved fixed respondent-level heterogeneity by including individual fixed effects in the models, there is a large, robust, and statistically significant positive relationship between violence exposure and risk aversion. Specifically, a rise of 1 homicide per 10,000 people at the municipality level, which is the average change between 2005 and 2009 across Mexican municipalities, significantly increased the likelihood of being risk averse in MxFLS3 by 1.5 percentage points, which represents a 5 percent increase from the average. We conclude that the removal of unobserved individual heterogeneity is imperative to generating unbiased estimates.[4]

Third, exploiting the richness of the MxFLS, in conjunction with its panel design, we explore the heterogeneity of the result with respect not only to fixed, but also changing characteristics of the respondents. This allows us to provide suggestive evidence regarding the important mechanisms driving the relationship between violence exposure and risk attitudes. While we find no evidence that the increase in risk aversion amongst the exposed is greater for individuals who have been adversely economically impacted by the violence, we do see significantly increased risk aversion amongst individuals with the largest changes in their reported feelings of fear and insecurity. These results suggest that the channel by which the conflict is changing risk attitudes is related to an individual's increased perception of potential victimization rather than as a result of a worsened financial environment.

Fourth, an environmental shock salient enough to potentially impact risk attitudes may induce behavioral responses such as migration. We find evidence of selective migration in the Mexico and mitigate its impact on interpretation of the results by assigning exposure intensity based on each respondent's location of residence before the onset of the surge in violence.

Fifth, it is plausible that the local intensity of the environmental shock under study may impact data collection efforts in that area. If this were the case the analytical sample would likely be non-randomly selected in a way that is correlated with the variable of interest. Without data on the respondents collected

[3]These results match the conclusions from the two prominent studies in this field, Voors et al. (2012) and Callen et al. (2014), which examine the impact of violence exposure on a similar risk aversion measure using cross-sectional data. Interestingly, while Callen et al. (2014) find no impact of violence on risk aversion generally, they report that, for those exposed to violence, risk tolerance under uncertainty increases but that certainty is preferred when available.
[4]The importance of removing individual level heterogeneity to assess the impact of an environmental shock on risk attitudes is also not specific to the Mexican context or violence. In a recent working paper by Hanaoka et al. (2015) they find that ignoring unobserved individual heterogeneity when examining the impact of exposure to the 2011 Great East Japan earthquake on risk attitudes significantly changes the size and direction of the estimated effect.

before the environmental shock it would be very difficult to assess the importance of this concern and impossible to correct without making very strong assumptions about the nature of the non-response. In this study, we are able to investigate whether attrition in our sample is correlated with local violence and find no evidence of this relationship overall or specific to particular observed characteristics. Furthermore, unique to the literature on violence and risk attitudes, by utilizing an individual fixed effect approach, any non-random attrition related to fixed observed or unobserved respondent characteristics is unable to bias the internal validity of the results.

Sixth, the measures of violence used in this study exploit the precise timing, location, and magnitude of the rise in violent crime which contrasts with previous studies that use binary markers of exposure and/or markers aggregated over many years (Voors et al., 2012, and Callen et al., 2014, for example).[5]

The next section provides a description of the increase of violence observed in Mexico since 2008. Section 3 describes the potential pathways between exposure to violence and risk attitudes and the current literature on this relationship. Section 4 details the data used in this study with a focus on the risk measures being employed as our main outcome of interest. Section 5 presents the empirical strategy and section 6 provides the results. Finally, in section 7 we discuss remaining threats to identification and robustness checks and section 8 concludes.

II. Background

Since early 2008, there has been a dramatic increase in violent crime in Mexico. Figure 1 provides the trend in the monthly homicide rate (per 10,000 inhabitants) from 2000 until 2011. The figure illustrates a stable homicide rate for almost a decade prior to 2007. The subsequent rise in 2008 homicides has been attributed to a change in policy of the Government of Mexico when President Felipe Calderón was inaugurated in December 2006 and soon after declared a war on drugs. The rise in homicides has been directly linked to the rise in violence due to battles between the government and drug cartels and battles among the cartels themselves. We will use municipality level homicide rates as a visible proxy for exposure to violent crime in the study community.

In contrast to previous tactics, Calderón's strategy with regard to the illegal drug trade in Mexico was intensely focused on direct confrontations with Organized Crime Groups (OCGs) drawing heavily on the use of the armed forces (Castillo et al., 2013; Molzán et al., 2012). The strategy had as its main goal to kill

[5]Moya (2017) makes a similar advancement to this aspect of the literature by using self-reported individual exposure to violence to estimate its effect on risk aversion in Colombia.

or capture the main leaders of the drug cartels. No more than ten days after taking office in December 2006, Calderón sent thousands of federal troops to the state of Michoacán to battle drug traffickers (Ríos, 2012). The initial success of this strategy can be seen from the break in the historical violence trend at the beginning of 2007. Unfortunately, this early success was not sustained, as only a few months later violence was back at its stable pre-2007 level.

The modest decline and then return to the long-term average of violent crime found in 2007 though was followed up by an unprecedented and arguably unanticipated tripling of the homicide rate between 2007 and 2011. It is believed that a major contributor to this significant change in the violence environment was an unintended consequence of the new war on drugs. Specifically, as Calderón's troops successfully displaced the leaders of the OCGs, the cartels, having lost their leadership, began to split apart into smaller cells and viscously fight amongst themselves for territorial control. Overall, the number of cartels operating in Mexico grew from six in 2006 to sixteen by 2011. In addition, once the outbreak happened, violence did not just escalate in the areas already exposed to cartel violence, but rather spread across the country, reaching areas that previously had no strategic value for drug-trafficking and were thus unaffected by the cartels (Guerrero-Gutiérrez, 2011). Thus, while violence has risen consistently over time, there is a great deal of variation in the changes in homicide rates across municipalities. Between 2005 and 2009, on average there was a 0.8 per 10,000 increase in the municipality homicide rates, but some areas suffered a 13 per 10,000 increase while others had a 14 per 10,000 *decline*. We exploit both the temporal and spatial variation to identify the effect of exposure to violent crime on people's levels of risk aversion.

The dispersion of violence in Mexico is provided in the maps contained in Figure 2. These maps show the municipal homicide rates per 10,000 inhabitants for 2002, 2005, and 2009. The first two maps provide a view of the conflict environment before Calderón took office. It is apparent that violence was highly concentrated along a few main drug trade routes. By 2009, however, the violence environment had noticeably been altered, with homicide rates increasing significantly and violence spreading across Mexico.

More than just the magnitude of the violence, the nature of crime in Mexico has changed as well. Given the increased competition between OCGs, these organizations have sought to build a reputation by committing and actively advertising increasingly brutal crimes (Beittel, 2013; Guerrero-Gutiérrez, 2011; Molzán et al., 2012). Also, as drug-trafficking profits have been squeezed by competition, the OCGs have diversified their financial sources and turned to crimes that directly affected the civil population, such as extortions, kidnappings and car thefts. Even executions have become more frequently targeted at civilians, particularly at authorities, reporters, and those not paying transit or extortion fees. In consequence, drug-related

violence has become embedded in society, triggering fear among the population (Díaz-Cayeros et al., 2011).

III. Violent crime and risk aversion: Pathways and prior evidence

Given the intensity of the escalation in violence, as well as, the OCG's increased focus on conspicuous uses of force and reliance on profits from personal crimes (e.g. extortion, kidnapping, car theft), there are several channels through which we may expect this new environment created by the Mexican drug war to affect people's levels of risk aversion. For instance, people more exposed to crime might perceive the environment as riskier and might behave in a more risk averse way to other choices with which they are confronted in order to reduce their overall exposure to risk. Alternatively, there is some psychological evidence of diminishing sensitivity that suggest people living in high risk environments act in a less risk averse way as they are not as concerned about risks that seem small relative to their general setting (Quiggin, 2003).

Another potential pathway is financial. Studies on the impact of the Mexican drug war have found that individuals with greater exposure to violence have suffered poorer economic outcomes (Dell, 2015; Robles et al., 2013; and Velásquez, 2015). Relying on different identification strategies, these studies find that the surge in crime has had a detrimental effect on the labor market participation and income of the Mexican population. The negative impact has been particularly strong for self-employed individuals, as they have been found to be the most targeted group for extortion and are the most likely to work in informal sector occupations which require more personal interaction (e.g. street vendors, small business owners, domestic services, etc.) (Velásquez, 2015). The economic literature suggests that risk aversion is negatively associated with income and wealth (Barsky et al., 1997; Guiso and Paiella, 2008) and thus through this channel we would expect that exposure to violence would increase levels of risk aversion.

Despite these potential pathways, the empirical literature on the causal effect of violent conflict on attitudes towards risk is still scarce. Voors et al. (2012) and Callen et al. (2014) have made the most significant contributions to this literature to date. Specifically, Voors et al. (2012) examines the impact of a civil war in Burundi on social, risk, and intertemporal choices. From 1993 to 2003 Burundi suffered through the most intense period of violence from a civil war between the two main ethnic groups. The authors utilize measures from experimental games collected in 2009 to study the cumulative effect of a decade's worth of violence on risk attitudes, amongst other preferences. The authors find that individuals who experienced more local violence from 1993-2003 exhibit significantly greater risk-seeking behavior six years after the end of that exposure period.

Callen et al. (2014), explores the impact of the violence that ravaged Afghanistan for nearly thirty years on risk attitudes collected in December 2010. Using a binary measure of local violence over the almost 8 year span of April 2002-February 2010, they find, in contrast to Voors et al., that there is no direct impact of exposure to violence on risk attitudes. However, they do report that when they randomly asked some individuals to recall an experience that caused them fear or anxiety in the past year these recalls influenced attitudes towards risk and certainty only among those who were exposed to violence. This finding suggests that the salience of the violence is a key mechanism linking exposure to an increase in risk aversion, and thus the fear generated by the victimization may be an important marker for its impact on risk attitudes.

In a recent, innovative study, Jakiela and Ozier (2016) compare risk attitudes of 14 to 31 year olds from the Busia District in Kenya's Western Province, for which the plausibly unexpected violence following he 2007 election lead some interviews to occur before and some to take place after this violent period. They find that individuals interviewed after the post-election violence subsided display higher rates of risk aversion although it is difficult to rule out the possibility that this result is also picking up the effect other environmental changes, in addition to violence, that occurred around the same time.

One potential explanation for the incongruent results of the current literature is that it is difficult to identify the effect of violence on risk attitudes relying solely on cross-sectional variation in exposure and aggregated measures of violence. The approach and data used in this paper strives to improve upon these limitations to contribute to our understanding of this topic.

IV. Data

Data for this research are drawn from two sources that contain information ideally suited for our purposes. First, we utilize the Mexican Family Life Survey (MxFLS), a rich longitudinal survey, representative of the Mexican population in 2002 at the national, urban, rural and regional level. Second, the National Institute of Statistics and Geography (INEGI) provides information on all reported homicides at the municipality and month level. We use this dataset to construct our measure of violent crime. Crucial for this study, the datasets cover periods both before and after the sudden outbreak of violence. By combining them we will be able to compare the outcomes of the same individual under different levels of violence, which will allow us to control for all unobserved time-invariant heterogeneity that might be correlated with exposure to violence and risk attitudes.

The MxFLS collects information on a wide range of socioeconomic and demographic indicators on individuals across three rounds. The baseline survey (MxFLS1) was conducted in 2002 and collected information on a sample of approximately 8,440 households and 35,600 individuals in 150 communities and 16 states throughout the country. A key feature is that the first follow-up (MxFLS2) was conducted in 2005 and 2006, when violence was relatively stable, and the second follow-up (MxFLS3) was largely conducted in 2009 and 2010[6], during the dramatic escalation of violence. In both follow-ups respondents' attitudes towards risk were elicited using a set of hypothetical questions on choices between gambles.

Another key feature of the MxFLS is its follow-up policy, according to which all baseline respondents and their children born after 2002 are sought for re-interview, including those who migrated within Mexico or emigrated to the United States. The MxFLS has had an outstanding success in achieving low levels of attrition: around 89% and 87% of the original baseline panel respondents were re-contacted in MxFLS2 and MxFLS3, respectively. Nonetheless, the relevant issue is whether our sample of interest is selected due to attrition in a way that is correlated with the change in the conflict environment. We perform this analysis in section VI and find no evidence that this potential issue is biasing our results.

Risk aversion measures

An established survey method to measure attitudes towards risk is to ask respondents to choose between gambles with different payoffs, in which options that offer a higher expected payoff also involve greater risk. Starting in its second wave, the MxFLS introduced a set of hypothetical questions of this sort. We rely on these questions to construct our measures of risk aversion.

In Figure 3, we present the set of hypothetical questions and the progression they followed in MxFLS2. The first decision a respondent faced was between an alternative of receiving an amount of $1,000 with certainty and an alternative of receiving either $500 or $2,000 with equal probability (in Mexico, the symbol $ stands for pesos[7]). Depending on the choice of the respondent, he or she next faced an alternative decision. If the sure amount of $1,000 was preferred, they will next have to decide between the sure amount of $1,000 and now a more attractive gamble of receiving either $800 or $2,000 with equal probability. In contrast, if the gamble offering either $500 or $2,000 was preferred, the subsequent choice they face was between that same gamble and now a gamble offering either $300 or $3,000. A few more questions in this pattern followed, and given all of their choices, individuals can be ranked according to their level of risk aversion. This ranking, shown at the bottom of the figure, has seven possible categories.

[6] Only 6% of the sample of panel respondents in Mexico was interviewed after 2010.
[7] At the time of MxFLS2, $ 1,000 was around US$ 90 and represented approximately 80% of the minimum monthly wage.

MxFLS3 contains the same type of questions, but the amounts and the progression changed with the aim of making the process simpler and increasing the respondent's understanding. Figure 4 shows the choices included in MxFLS3. One of the innovations introduced in MxFLS3 was to include a first question aimed at evaluating whether the respondents understood the choices they faced. This question asked the respondents to choose between a gamble of receiving either $2,500 or $5,000 with equal probability and a dominated sure amount of $2,500. If the respondent preferred the latter, then the question was explained again. If he or she still preferred the later then this may indicate that the respondent is extremely risk averse, or "gamble averse", as he or she preferred not to select the gamble even though it was costly decision. However, an alternative interpretation of this behavior is that it indicates a lack of understanding of the question. In order to push this further, a last question was asked in which both alternatives in the gamble were strictly greater than the sure amount. Even in this case, there are respondents who preferred the sure amount.

If the respondent is not "gamble averse", then the next question he or she faced was between a gamble of receiving either $2,000 or $5,000 and a sure amount of $2,500. If the sure amount was chosen, then no more questions were asked. If the gamble was selected, the respondent then had to choose between the same sure amount and a less attractive gamble. If the sure amount was chosen, then no more questions were asked. This procedure continued for a few more questions and generated the risk aversion index shown at the bottom of Figure 4.

As these types of measures are expected to be a noisy signal of the actual risk aversion of individuals (Kimball et al., 2009), separating small changes in risk aversion from measurement error will prove to be difficult. Our approach to deal with this challenge is to focus on changes at the extremes of the distribution by classifying individuals as "most risk averse" or not. Since the exact questions changed between waves, caution should be exercised when interpreting the results, as a change in categories between waves does not necessarily mean that the respondent's absolute level of risk aversion changed. Interpretation of the transitions is relative to what happened in the population in general. For example, individuals changing from "not most risk averse" in MxFLS2 to "most risk averse" in MxFLS3 does not mean they necessarily became more risk averse, but rather that their level of risk aversion is on a more positive (or less negative) trend relative to those categorized as "not most risk averse" in both waves.

There are several different ways to classify respondents as most risk averse or not, the classification we use is based on the difference between the sure amount and the expected value of the gamble that was declined in favor of the sure amount. This information provides us with a lower bound of the respondents' risk

premium, which is the difference between the certainty equivalent and the expected value of the gamble. In MxFLS2 we classify as "most risk averse" those with a risk aversion index equal to 5, 6 or 7. Individuals in this group have a risk premium greater than $400. In turn, in MxFLS3 we classify as "most risk averse" those with a risk aversion index equal to 5. Individuals in this category have a risk premium greater than $1,000. Also included in the category of "most risk averse" in MxFLS3 are the 13% of individuals classified as "gamble averse" (i.e. with a risk index of 6 or 7 in MxFLS3). While this seems like the most natural group for these individuals, in section VII we also perform the analysis designating the "gamble averse" respondents as not being "most risk averse" and alternatively re-estimating the main results excluding "gamble averse" respondents all together. In both cases the results are qualitatively and quantitatively equivalent to the initial designation of the "gamble averse" respondents. In general defining these classifications is not straightforward, and for that reason in section VII we also confirm the robustness of our results to several different classifications of "most risk averse".[8]

Our analytical sample includes those individuals who were 15 years old or older at baseline and answered the hypothetical questions aimed at measuring risk aversion in both MxFLS2 and MxFLS3,[9,10] Table 1 shows the distribution of the risk aversion indexes in both waves for our analytical sample. According to our preferred classification, 17.5% of our sample is most risk averse in MxFLS2 and 44.1% in MxFLS3. Transitions in risk attitudes between MxFLS2 and MxFLS3 could potentially be attributed to noise or to the many other factors that determine risk attitudes that may have changed over the four-year period between surveys.[11] Our goal is to establish whether the change in the conflict environment constitutes part of the explanation.

In order to conduct our analysis, we pair the MxFLS survey with the month and municipality-level homicide dataset collected by INEGI. This dataset contains the official reports of all intentional homicides. The homicide rate is used to capture the overall crime environment created by the drug war. Researchers

[8] Appendix Table A1 explores the relationship between our measure of "most risk averse" and behaviors that represent some degree of risk-taking. Specifically, we examine if individuals measured as "most risk averse" in MxFLS2 are more or less likely to be engaged in risky behaviors in MxFLS3. The first risky behavior we examine in columns 1 and 2 is cigarette consumption. We find that individuals who are "most risk averse" in MxFLS2 are smoking significantly less by MxFLS3. In columns 3 and 4 we add in two risky behaviors related to economic decisions: migration and self-employment. In these columns we focus on our male sample as their labor decisions typically determine the economic wellbeing of their household and migration for males is more likely to represent moving to pursue economic opportunities and self-employment is more likely to reflect business ownership. The results for this analysis, found in columns 3 and 4 of Table A1, show that being "most risk averse" in MxFLS2 is negatively related in sign to each of the risky behaviors in MxFLS3 and statistically significantly so for migration.
[9] We require that individuals were interviewed in baseline and were at least 15 years old at the time of that interview because in our empirical strategy we will control for individuals characteristics in previous waves, and some of those characteristics are only measured for those who are at least 15 years old.
[10] Appendix Table A2 provides descriptive statistics for our analytical sample.
[11] Appendix Table A3 provides the risk attitudes index transition matrix.

have shown that the INEGI intentional homicide data matches the temporal and geographic heterogeneity of reports of homicides specifically related to drug-related confrontations collected by the government (Heinle et al., 2015). Moreover, a relationship has been established between homicide rates and other types of crimes committed by traffickers' organizations (Guerrero and Gutiérrez, 2011; Molzán et al., 2012). Exploiting the richness of the MxFLS, we can provide further evidence that homicide rates seem to be a useful measure of the general crime environment. At the time of the MxFLS3 interview, people living in municipalities that experienced greater changes in homicide rates between 2005 and 2009 were more likely to report feeling less safe than 5 years ago and more scared of being attacked (see Table A4 of the Appendix, columns 1-2))[12].

Nonetheless, concerns regarding potential measurement error in the INEGI homicide dataset might remain. With respect to random measurement error, there are good reasons to think that homicides are less prone to this problem in comparison to other indicators of violence such as physical injury or property loss. Homicides are more reliably reported given that they measure an extreme endpoint of individual violence and are homogeneously defined across regional boundaries (Shrader, 2001). The presence of systematic measurement error is also a potential concern, but this does not seem to be an issue in this case as the INEGI dataset closely correlates with other datasets that rely on alternative sources such as the government or journalist reports (Heinle et al., 2015, Molzán et al., 2012).

V. Identification strategy

V.1. Endogenous Migration

A potentially important concern when trying to establish causality between an environmental shock and risk attitudes is endogenous migration. Intuitively, exposure to a shock may cause migration that is selected on an individual's risk attitudes. In our context, for example, this would arise if a more risk averse individual were more likely to move away from municipalities with higher levels of violence. If this was the case and migration was ignored in the identification strategy, the relationship between crime and risk tolerance would be upward biased. To examine whether migration responded to the change in the conflict environment in Mexico we estimate the following model:

$$M_{ijt} = \alpha_0 + \alpha_1 \Delta Hom_j + \alpha_2 X_{ij} + \beta(X_{ij} \times \Delta Hom_j) + \gamma_t + \lambda_j + \varepsilon_{ij} \quad (1)$$

[12] The same conclusion is reached if we use contemporaneous measures of homicide rates at the time of the MxFLS3 interview instead of changes between 2005 and 2009.

where M_{ij} is a binary variable equal to 1 if the respondent was interviewed in a different municipality in MxFLS2 and MxFLS3, ΔHom_j is the change in the homicide rate between 2005 and 2009 in MxFLS2 municipality of residence *j*, X_{ij} are individual and household characteristics measured in MxFLS2 and include: age, age squared, years of education, marital status, employment status, earnings, household characteristics and rural residence, γ_t captures date of interview fixed effects, which include a wave fixed effect and year and month of interview fixed effects, and λ_j represents fixed effects for the municipality of residence in MxFLS2. Running this regression excluding the interacted terms, α_1, provides evidence on whether overall migration is related to the change in violence. More importantly to the potential bias caused by endogenous migration, we evaluate whether conflict related migration was systematically different for individuals with certain characteristics. Evidence on this is provided by the set of coefficients represented by β in equation 1.

Table 2 presents the results of this analysis for our analytical sample. While there is not a significant relationship between potential violence exposure and migration in general, we do find evidence of violent crime induced selective migration that is related to the ruralness of the respondent's location of residence and the respondent's martial status. Specifically, it appears that individual's living in rural areas are more likely to move out of their municipality than individuals living in urban areas in response to increased crime and that being single increases the probability of moving as a response to local violence. Since these observed characteristics, and the potential unobserved characteristics, driving non-random migration may have a relationship with the evolution of an individual's risk attitudes, the theoretical bias of endogenous migration must be accounted for to generate unbiased estimates of the impact of violence on risk attitudes.

In order to shield our estimates from the bias of endogenous migration, we follow an intent-to-treat approach in our empirical specification. To do this an individual is assigned a conflict exposure level based on their municipality of residence in MxFLS2, before the rise in crime, rather than based on his/her current municipality of residence. Thus, the intensity of violence exposure assigned to a respondent is independent of any migration decisions made as a response to crime.

V.2. Empirical specification

The empirical strategy can be summarized in the following regression framework:

$$Y_{ijmt} = \beta_1 Hom_{jt} + \beta_2 X_{i,t-1} + \theta_i + \gamma_t + \lambda_m + \varepsilon_{ijmt} \quad (2)$$

where Y_{ijt} is a binary variable equal to 1 if individual *i*, living in municipality *j* at the time of the MxFLS2 interview, currently living in municipality *m*, and interviewed at time *t*, is in the most risk averse category, Hom_{jt} is the homicide rate in municipality *j* over the 12 months prior to the MxFLS interview, X_{it} are the time-varying characteristics measured during the previous wave[13], θ_i captures individual fixed effects, γ_t captures date of interview fixed effects, which include a wave fixed effect and year and month of interview fixed effects, and λ_m represents fixed effects for the municipality of current residence.[14]

VI. Results

VI.1. Using Cross-Sectional Data

Before moving to the main results from the full specification described in equation 2, it is useful to present results that are directly comparable with existing studies that use cross-sectional variation in exposure to identify the effects on risk. This analysis is conducted by running equation 2 separately for MxFLS2 and MxFLS3 and thus also removing the individual fixed effects and wave fixed effects. The results of these cross-sectional regressions are found in columns 1 and 2 for the MxFLS2 data and columns 3 and 4 for the MxFLS3 data of Table 3.

Column 1 and 2 of Table 3, which only uses the MxFLS2 data, mirrors the method most commonly employed in this literature of analyzing persistent levels of violence. In these regressions most of the variation in violence comes from differences in crime rates that have existed for over a decade. In addition, the majority of the literature that examines the impact of local violence on risk attitudes assigns each individual in an area the same cumulative violence exposure score and thus cannot employ area fixed effects at the level of the violence measure, making column 1 of Table 3 the most direct comparison. Using this approach we find that violent crime is associated with significantly increased risk tolerance, similar to the conclusions of Voors et al. (2012). One concern with this analysis is that it could possibly be picking up the fact that individuals with more risk averse attitudes are more likely to locate in municipalities with lower potential violence. Do to the fact that individuals are interviewed on different dates in the MxFLS and that the INEGI provides monthly homicide data, we partially address this issue by including a municipality fixed effect into the analysis. These results are found in column 2 of Table 3. The inclusion of

[13] In an attempt to limit the possibility that time-varying individual characteristic trends related to violence exposure bias our results, we add as controls time-varying characteristics (marital status, number of children, years of education, employment status, employment category, earnings and household characteristics), measured during previous waves. We use previous wave characteristics to ensure the controls are not endogenous to violent crime.
[14] The main results are provided with and without the municipality of current residence fixed effects as it may be endogenous to violent crime exposure.

the municipality fixed effect greatly attenuates the coefficient on violence exposure, which remains negative but is now insignificant, similar to the comparable results in Callen et al. (2015).

An alternative to using variation in violence that comes from a long-standing conflict or persistent situation, which may be particularly susceptible to endogenous behavioral responses, is to identify a plausibly exogenous source of change in the violence environment. As detailed previously, this type of unanticipated shift in the magnitude and location of violent crime occurred in Mexico in the last few years. Thus, an alternative approach would be to exploit this natural experiment by looking at the impact of violence on risk attitudes during the period after this unprecedented change in the violence in Mexico occurred. The results from this strategy are found in column 3 and 4 of Table 3 and imply that no significant relationship exists between risk attitudes and exposure to local violent crime.

The main concern that remains with both of these cross-sectional analyses is that the estimates may be biased by the unobserved individual heterogeneity that determines the level of crime they are exposed to, when they are surveyed, if they complete that survey, and how there risk attitudes evolve over time. Our identification strategy, by exploiting the panel nature of our survey to compare the risk aversion levels of the same individuals before and after the change in the conflict environment, will control for any of the unobserved individual heterogeneity that is fixed over time. If this unobserved heterogeneity is not leading to bias in the cross-sectional results, we should find that the cross-sectional estimates do not substantially differ from the preferred specification we outlined in equation 2.

VI.1. Using Longitudinal Data

The results of conducting equation 2 on our analytical sample are shown in columns 5 and 6 of Table 3. The estimates in both columns provide evidence that individual heterogeneity was a source of bias in the cross-sectional analyses and that exposure to local violence is associated with a significant and substantial increase in risk aversion. Specifically, these results suggest that an increase of 1 homicide per 10,000 people, which is similar to the average change between 2005 and 2009 across municipalities, increased the likelihood of being in the most risk averse category in MxFLS3 by 1.5 percentage points or a 5% increase in being risk averse as compared to the average.

We continue our analysis by testing the level of heterogeneity of this effect on the population. To do this we selected individual demographic and economic characteristics, measured in MxFLS2 that could plausibly affect an individual's level or type of exposure to violence and used them to run a fully interacted version of equation 2. The results of this heterogeneity analysis are found in Table 4.

The first difference we examine is between women and men. In the Mexican context there are several reasons to believe men and women may have different levels of expected exposure to crime. For example, as the labor participation of men is much greater than that of women they may be more exposed to extortions, kidnappings and business thefts. In addition, the type of crimes and violence faced by women and men may differ as well. It has been documented, for example, that women face hire rates of violence in Mexico that is personal in nature (United Nations 2011). The estimated difference in the impact of violence on risk attitudes between men and women can be found in Table 4, column 2. Here we see again that overall there is a positive relationship between local violent crime exposure and risk aversion, but that the effect does not differ significantly by gender.

Another dynamic of the violence in Mexico is that the change in the conflict environment was not homogeneous across the country. Since most of the cartels profits are generated by drug-trafficking activities rather than by drug production, part of President Calderón's change in strategy was to reduce the focus on crop eradication and target drug-trafficking centers including urban warehouses and highway transportation routes (Castillo et al., 2013; Llorente et al., 2014). It is thus possible that the type and severity of the crimes also differ between rural and urban areas. To evaluate whether the results vary between these areas, we fully interact equation 2 with the urban/rural status of the individual's municipality of residence in MxFLS2. These results are found in column 3 of Table 4 and provide no evidence of a difference in the impact of violence on risk attitudes by urban/rural status.

A third piece of heterogeneity we explored was socio-economic status (SES). Individuals with different levels of socio-economic status may experience local violence in very different ways. For example lower SES individuals may be unable to avoid exposure and potential victimization due to relying on public transportation, having inflexible work schedules, and not being able to afford protection service at home or at work. It is also possible that within a municipality the location the crime is actually occurring is in the low or high income neighborhoods, thus the violence measure in the model does not reflect actual intensity of exposure. Alternatively, if violent crime during this period increased in all areas of the municipality the relative change may be bigger for areas that previously had the lowest rates. To proxy for low SES we identify respondents living in a household in the bottom quartile of per capita expenditure (PCE) in MxFLS2. The results when exploring heterogeneity by household per capita expenditure are found in column 4 of Table 5. The estimates for this analysis suggest that, unlike the rest of the respondents, the risk attitudes of individuals living in households in the lowest quartile of PCE are not sensitive to the municipal homicide rate.

This result is consistent with a few different potential explanations. First it could be the case that there is a difference in the location of the violence within a municipality that is related to SES, either in magnitude or relative to previous levels (i.e. violence was more intense in magnitude, or relative to previous levels, in high income neighborhoods compared to low income neighborhoods). Second, if the reason risk attitudes are reactive to exposure to violence is related to increased fear/anxiety/instability, it is possible that low SES individuals may already be past some threshold on that dimension such that increased local violence is unable to make a significant difference in those preferences. Third, it is possible the risk attitude index is a more noisy measure for low SES individuals.

The last area of heterogeneity based on fixed characteristics was examined in order to start providing clues into the mechanism driving the relationship between exposure to violence and increased risk aversion. One of the main channels that could be generating this relationship is financial. If the increase in local violence also led to decreased economic activity and opportunity, it is possible that this weaker labor market is the element to which risk attitudes are reacting. In the Mexican context there is evidence that increased violence has caused poor economic outcomes for a certain subset of the population.

Consistent with anecdotal evidence that the self-employed have suffered the most economically from reduced night time commerce in commercial centers caused by increased violence, Velásquez (2015) finds that exposure to violence significantly reduced the earnings of self-employed men and the labor market participation of self-employed women. This difference in experience for the self-employed offers us the first opportunity to test if the focal pathway of municipal violence on risk attitudes is financial. In column 5 of Table 4 we explore if the risk attitudes of the self-employed are more strongly impacted by local violence than other respondents and find no evidence to support this hypothesis. While this result is suggestive that economic wellbeing is not the main mechanism behind the increased risk aversion of those living in more violent municipalities, we explore this further by examining heterogeneity related to changes in an individual's economic wellbeing.

In order to more fully examine if it is the individuals that suffered economic shocks as a result of the increase in violence that are driving the relationship between risk aversion and local violent crime exposure, we full interact our main model, equation 2, with two measures of time-varying economic wellbeing. The intuition for this analysis is that if the change in risk attitudes caused by local violence is a function of the adverse effect violence is having on economic wellbeing, then individuals who have experienced the worst changes in their labor market/financial outcomes during the escalation in violence should display the largest effect.

First, we explore if the effect of violence on risk aversion differed for individuals who lost their job between MxFLS2 and MxFLS3. The results for this analysis are presented in column 2 of Table 5 and provide no evidence that individuals that became unemployed during the time of the escalation of violence are differentially contributing to the impact of exposure to violent crime on risk aversion. The second measure we use to capture the relationship between financial loss during the surge in violence and risk attitudes is changes in household per capita expenditure. Specifically, we examine the risk attitudes of individuals from households that were in the bottom quartile of change in per capita expenditure between MxFLS2 and MxFLS3. The estimates of this heterogeneous treatment effect are provided in column 3 of Table 5 and further suggest that economic wellbeing is not the mechanism through which local violence is changing risk attitudes.

An alternative explanation for the positive relationship between exposure to violence and risk aversion is that individuals are responding to the insecurity in their environment by reducing risk in choices they have direct control over. If this were the case we would expect individuals who perceive that they are at the highest risk for victimization would be the most likely to respond to the risk attitudes survey instrument in a risk averse way. To investigate this hypothesis we look at if individuals who have become fearful of being attacked at night between MxFLS2 and MxFLS3 are those whose risk attitudes are most sensitive to local violence exposure. The results for this analysis are shown in column 4 of Table 5. These estimates suggest that the percentage point increase in risk aversion amongst respondents who report becoming fearful of victimization during the escalation of violence is more than double the size as compared to the rest of the sample. Taken altogether the estimate in column 5 of Table 4 and the results in Table 5 provide suggestive evidence that the pathway through which local violent crime is impacting risk attitudes is through the fear of victimization rather than financial hardship.

VII. Threats to Identification

The main threat to identification that exists given that our empirical strategy utilizes an individual fixed effects approach within a natural experiment framework, is that the diverse geographic and sharp temporal variation in violence found in Mexico was not unanticipated and/or was correlated with other underlying trends related to an individual's level of risk aversion. While we contend that this is an unlikely scenario given the suddenness and political origins of the outbreak of violence, we believe it is important to lay out the evidence that exists regarding this potential concern.

With regard to the hypothesis that the change in the conflict environment was unanticipated and unrelated to prior trends in crime/insecurity, the MxFLS data on self-reported feelings of safety provide supporting

evidence. When estimating models at the individual level, we find no correlation between self-reported feelings of current safety or trends in feelings of safety in MxFLS2 (i.e. pre-escalation of violence) and the subsequent changes in homicide rate that actually occurred between 2005 and 2009 (see Table A4 of the Appendix, columns 3-4). This suggests that municipalities that would subsequently be exposed to larger increases in violence were not already less safe or on a downward trend in perceived security.

More generally, Brown (2016) and Velasquez (2015), explicitly explore if linear trends in pre-violence municipality characteristics such as education, institution, infrastructure, economic activity, demographics, among other factors, predict the level and location of the escalation in violence. Specifically, they use over 30 pre-escalation of violence trends for the 136 baseline MxFLS municipalities to predict both the 2009 municipal homicide rate and the change in the municipal homicide rate between 2005 and 2009. The pre-outbreak of violence trends were generated using the IPUMS samples of the 2000 and 2005 Mexican censuses and the MxFLS1 and MxFLS2 survey waves. The findings from this analysis strongly suggest that previous municipal trends do not predict future violence[15].

While these two pieces of evidence suggest that there are not linear unobserved municipal trends that are correlated with the homicide rate, they would not be able to detect a non-linear municipal characteristic change that occurred simultaneously or closely in time to the escalation of violence and followed a similar geographic pattern. Thus, our results should be considered causal only under the assumption that this type of shift did not occur.

One potential event that occurred between the MxFLS2 and MxFLS3 survey waves and could possibly fit this description is the Great Recession. Specifically, if the areas most economically impacted by the Great Recession also happened to be the locations with the largest change in violence this would violate our identification strategy. Several studies of this issue, though, have confirmed that the geographic heterogeneity of crime in Mexico does not correspond to the differential regional magnitude of the Great Recession (Ajzenman et al., 2015; Velásquez, 2015). Despite the lack of evidence to corroborate this potential issue, we next conduct robustness checks on our main result from column 6 of Table 3, to help alleviate concerns that the Great Recession biases our findings.

The first test we run is to include controls for the local economic environment into equation 2 in order to potentially mitigate any bias caused by the Great Recession. Specifically, we add municipality-year level

[15] Of the 62 independent variables tested only 3 coefficients are significant at the 10 percent level, which are fewer than what would be expected by chance, and a joint F-test of all the estimates is insignificant. These results are replicated in Appendix Table A5.

electricity use (kWh), manufacturing industry and retail sector characteristics (# of establishments, # of employees, gross total production, total value added) for each municipality in 2004 (assigned to MxFLS2 observations) and 2009 (assigned to MxFLS3 observations), and state-year level GDP.[16] The estimate from this analysis, which can be found in column 2 of Appendix Table A6, is slightly attenuated in magnitude as compared to the main specification, but is statistically indistinguishable from the main result.

A second robustness check that we conduct is to exclude from the sample respondents that live in regions of Mexico that are most likely to be exposed to the adverse effects of the Great Recession. Mexico's economic decline during the Great Recession is due to its economic relationship with the United States. Since, this relationship is likely strongest along the U.S.-Mexico border, we drop from our analysis respondents from states along the northern border with the U.S.[17] The results from this subsample are provided in column 3 of Appendix Table A6 and confirm the estimates from the main analytical sample.

Another potential threat to the validity of our results is our choices with regard to the creation of our main dependent variable. The first challenge is the appropriate way to assign risk aversion to the "gamble averse" respondents. While in our main results we include the "gamble averse" individuals in the "most risk averse" category, we have also explored whether our results are robust to two alternative ways of treating the "gamble averse": assuming they are not in the "most risk averse" category and excluding them from the sample altogether. Results, shown in Panel A of Appendix Table A7, confirm that our estimate of the impact of violence on risk aversion is statistically unchanged using either of these two alternative approaches. The second sensitivity analysis of our dependent variable is a test of using five alternative classifications of the "most risk averse" category in both MxFLS2 and MxFLS3. Results are reported in Panel B of Appendix Table A7.[18] The robustness of our estimate to these alternative classifications is also confirmed.

The final issue that one faces when using survey data to study a major environmental shock is the possibility of selective attrition. Moreover, despite MxFLS' successfully low levels of attrition in general, it is important to evaluate whether selection in our analytical sample is correlated specifically with changes in the levels of violence. The concern is that if there is selective attrition related to potential violence exposure our sample would no longer be representative. To test for potential selection bias from attrition we estimate the same linear probability model as we used to examine endogenous migration, equation 1, and replace the

[16]This analysis should be viewed with caution as these economic controls are potentially endogenous in a way that would bias our estimates towards zero, as previous research has documented the negative economic impact of the War on Drugs in Mexico (Robles et al., 2013; Dell, 2015; and Velásquez, 2015) and this could be part of the causal channel that influences the risk attitudes of individuals exposed to local violence.
[17] Specifically, respondents from the Mexican northern border states in the MxFLS (i.e. Coahuila, Nuevo León, and Sonora) are dropped from the sample.
[18] In each specification the "gamble averse" individuals are included in the "most risk averse" category.

dependent variable with an indicator equal to 1 if we have the necessary survey responses from the individual for our main analysis in MxFSL2 but not in MxFLS3. Results are reported in Appendix Table A8. We do not find evidence that attrition is on average correlated with the change in violence (column 1), or within any subgroups that would indicate non-random crime-related attrition (column 2).

VIII. Conclusion

This research has examined the impact of the Mexican drug war on risk attitudes to shed new light on the question of whether and how an individual's attitudes towards risk respond to changes in their environment. We directly address several empirical challenges that have impeded progress in this literature. Using plausibly exogenous spatial and temporal variation in exposure to violent crime in combination with longitudinal survey data, we compare an individual respondent's measured attitude towards risk before the onset of Calderon's war on drugs with the same individual's attitudes after the onset. The empirical estimates thereby take into account all individual-specific characteristics that are fixed and affect attitudes towards risk. Our identification strategy not only takes into account individual-specific time-invariant heterogeneity that may be correlated with exposure to violence and risk attitudes but also directly deals with selective migration that is related to violence and risk attitudes. We also provide evidence that failing to control for unobserved individual heterogeneity results in substantially biased estimates of the relationship between risk attitudes and an environmental shock in our context.

We find that exposure to local violence significantly increases risk aversion. In particular, our results suggest that an increase of 1 homicide per 10,000 people, which is similar to the average change between 2005 and 2009 across municipalities in Mexico, increased the likelihood of being in the most risk averse category in MxFLS3 by 1.5 percentage points or a 5% increase in being risk averse as compared to the average. Moreover, our results do not seem to be driven by respondents that have suffered the most economically due to the escalation of violence, but rather it is those who face the highest perceived potential risk from the violence that are most likely to become more risk averse.

In addition to increasing our understanding of the ways risk attitudes evolve in response to changes in our environment, our results also provide evidence of another hidden cost of violent conflict on the wellbeing of the exposed. Increased risk aversion has been shown to be negatively associated with engaging in riskier but more profitable endeavors related to investment decisions, occupational choice and migration (Barsky et al, 1997; Bellemare and Shearer, 2010; Charles and Hurst, 2003; Kan, 2003; Kimball et al., 2008). This suggests that risk aversion can be detrimental to wealth accumulation and thus violent conflict and

insecurity have another pathway through which they can impact a country's long-term economic development.

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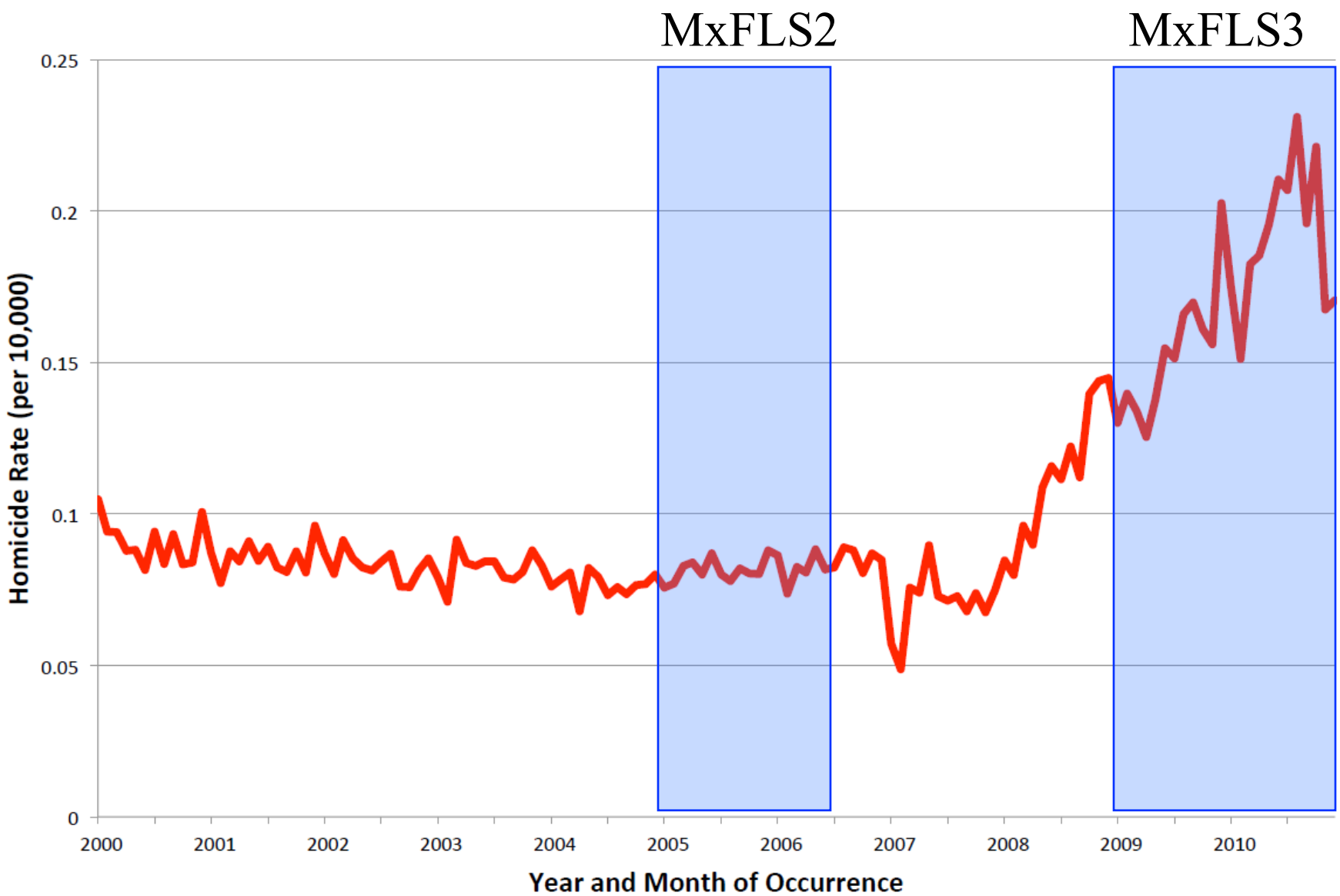
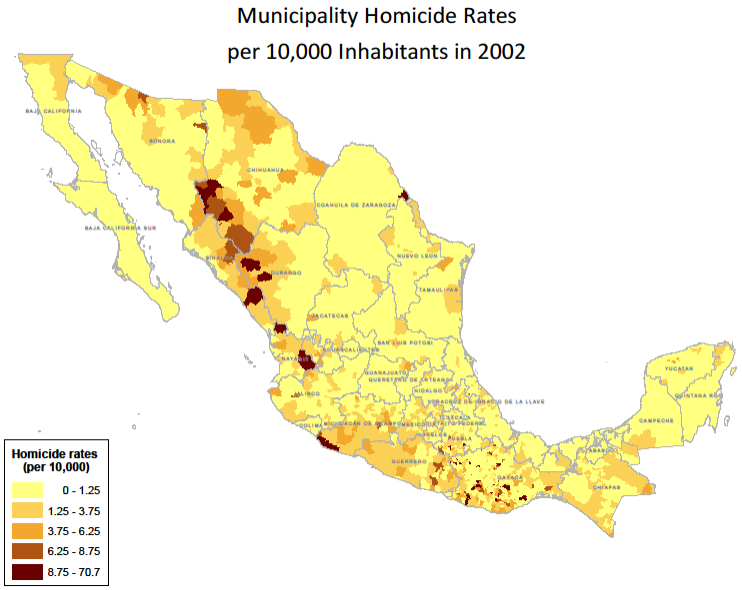
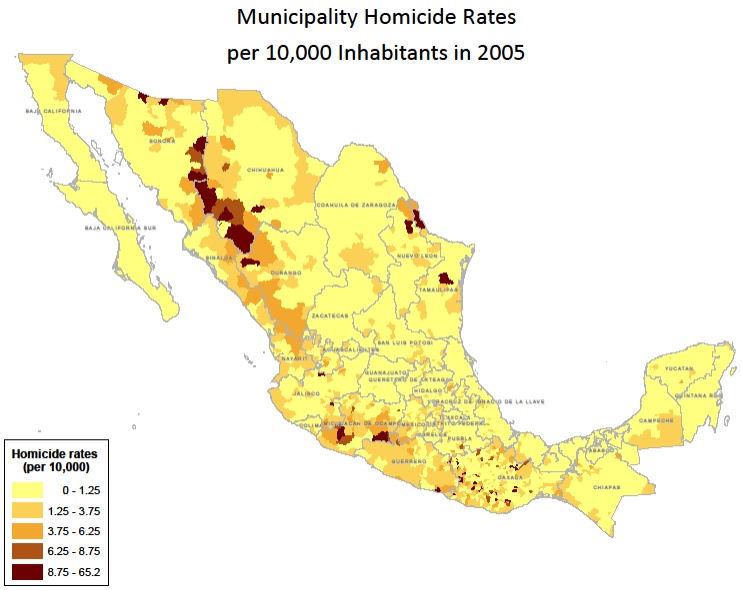
Figure 1: Monthly Homicide Rate (per 10,000)



Notes: Data on all reported homicides are collected by the National Institute of Statistics and Geography (INEGI)

Figure 2: Municipality Homicide Rates (per 10,000) by Year





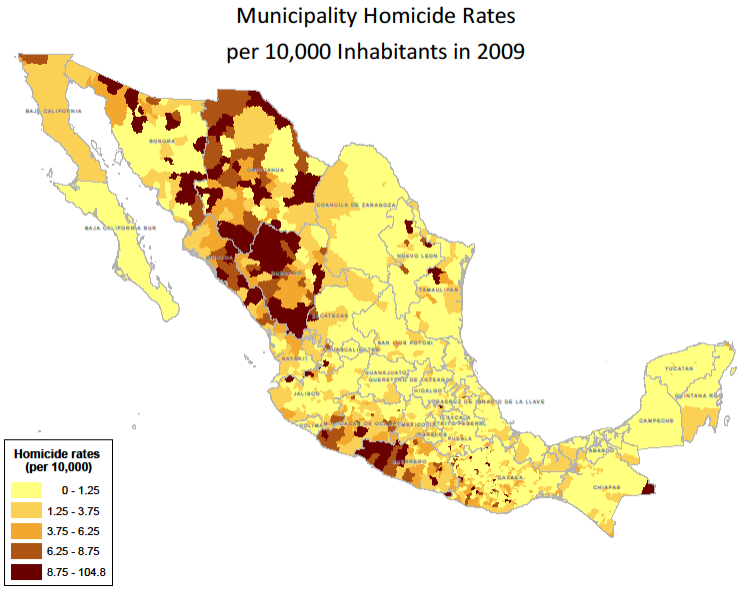
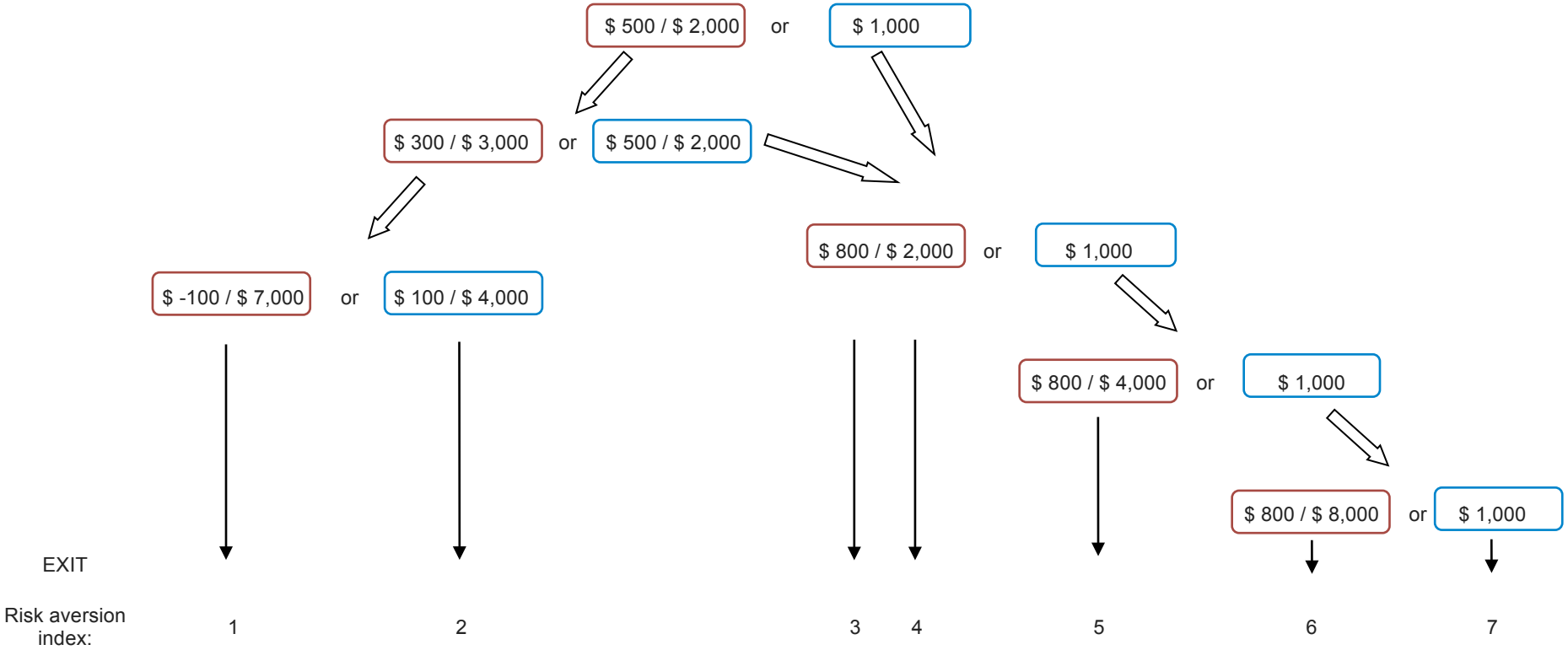
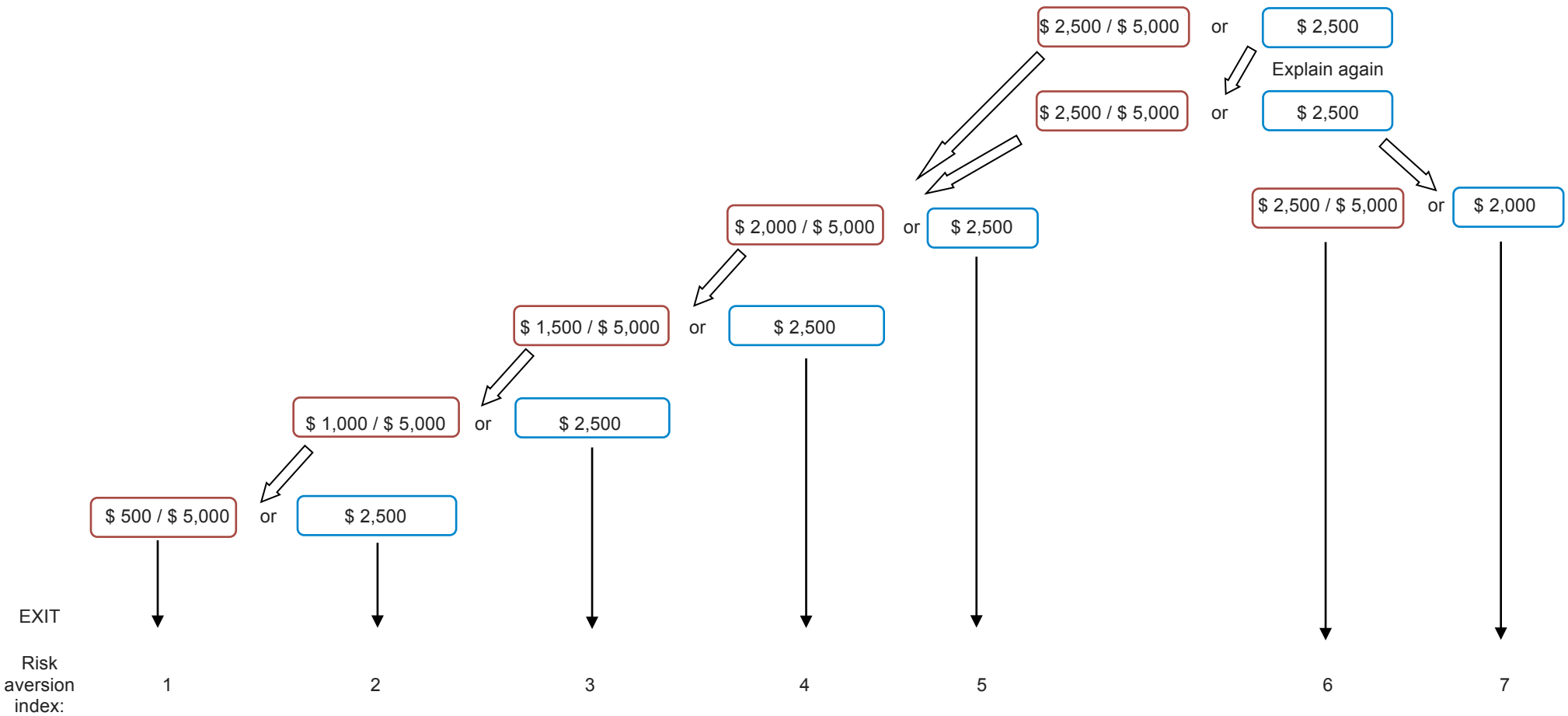


Figure 3: Series of Binary Choices over Hypothetical Gambles in MxFLS2



Notes: In Mexico, the symbol $ stands for Mexican pesos. In this figure $ is also used to represent pesos.
The risk aversion index goes from 1 to 7 and is increasing in risk aversion.
The risk index categories 3 and 4 share the same exit option but corresponds to different choices:
- The risk index category 3 corresponds to the following choices: $500 / $2,000 in the first and second choices and $800 / $2,000 in the third choice.
- The risk index category 4 corresponds to the following choices: $1,000 in the first choice and $800 / $2,000 in the second choice.

Figure 4: Series of Binary Choices over Hypothetical Gambles in MxFLS3



Notes: In Mexico, the symbol $ stands for Mexican pesos. In this figure $ is also used to represent pesos.
The risk aversion index goes from 1 to 5 and is increasing in risk aversion. We call "gamble averse" those in category 6 and "gamble averse – pay" those in category 7.

Table 1: Distribution of risk aversion index

Index Number	Index Description	MxFLS2
1	Lowest risk aversion	33.0%
2	Second lowest risk aversion	4.9%
3	Third lowest risk aversion	8.3%
4	Fourth lowest risk aversion	36.3%
5	Third highest risk aversion	7.3%
6	Second highest risk aversion	1.8%
7	Highest risk aversion	8.4%
Observations		11,348

Index Number	Index Description	MxFLS3
1	Lowest risk aversion	22.9%
2	Second lowest risk aversion	4.7%
3	Third lowest risk aversion	11.1%
4	Fourth lowest risk aversion	17.2%
5	Highest risk aversion	30.9%
6	Gamble aversion	5.8%
7	Higher gamble aversion	7.4%
Observations		11,348

Table 2. Relationship Between Migration and Homicide Rate

Dependent variable equals 100 if respondent was interviewed in a different municipality between MxFLS2 and MxFLS3 and 0 otherwise

	(1)	(2)
Δ in Municipal Homicide Rate between 2009	-3.134	-6.410
	[4.539]	[5.006]
Δ *Homicide Rate between 2009 & 2005 interacted with MxFLS2 characteristics:*		
Female		0.197
		[0.335]
Age		0.006
		[0.035]
Age Squared		0.000
		[0.000]
Married or cohabits		-0.501**
		[0.221]
Number of children		0.021
		[0.016]
Education (years)		0.044
		[0.030]
Worked last week		0.269
		[0.291]
Self-employed		-0.120
		[0.118]
Earnings (quartic root)		-0.011
		[0.029]
HH size		-0.018
		[0.048]
Number of children of other HH members		0.031
		[0.084]
HH PCE (quartic root)		0.062
		[0.068]
Rural		2.074**
		[0.963]
Scared of being attacked at night		-0.050
		[0.176]
Mean dep. variable	3.41	3.41
Observations	11,309	11,309

Notes: Standard errors clustered at the municipality level. *** p<0.01, ** p<0.05, * p<0.1. All models control for individual characteristics, household characteristics, date of interview, and municipality fixed effects.

Table 3: Impact of violent crime on risk aversion

	Most risk averse = 100					
	Only MxFLS2	Only MxFLS2	Only MxFLS3	Only MxFLS3	MxFLS2 & MxFLS3	MxFLS2 & MxFLS3
	(1)	(2)	(3)	(4)	(5)	(6)
Homicide rate	-2.203***	-0.426	0.373	-0.368	1.472***	1.525***
	[0.772]	[1.096]	[0.329]	[0.588]	[0.465]	[0.481]
Mean dep. variable	17.51	17.51	44.14	44.14	30.82	30.82
Observations	11,348	11,348	11,348	11,348	22,696	22,696
Number of individuals	-	-	-	-	11,348	11,348
Individual Fixed Effects	NO	NO	NO	NO	YES	YES
Municipality Fixed Effects	NO	YES	NO	YES	NO	YES

Notes: Standard errors clustered at the municipality level. *** p<0.01, ** p<0.05, * p<0.1. All models control for individual characteristics and household characteristics and date of interview fixed effects. Wave fixed effects included when using multiple waves.

Table 4: Heterogenous impact of violent crime on risk aversion by individual characteristics measured before the escalation of violent crime

	Most risk averse = 100				
	(1)	(2)	(3)	(4)	(5)
Homicide rate	1.525***	1.519***	1.482***	1.839***	1.462***
	[0.481]	[0.492]	[0.556]	[0.501]	[0.482]
Homicide Rate*I(Male=1)		0.030			
		[0.528]			
Homicide Rate*I(Live in Rural Locality in MxFLS2=1)			-0.095		
			[0.922]		
Homicide Rate*I(Bottom Quartile of PCE in MxFLS2=1)				-1.02	
				[1.097]	
Homicide Rate*I(Self-Employed in MxFLS2=1)					-0.008
					[1.045]
P-value for F-Test (Homicide Rate + Homicide Rate Interaction=0):		0.01	0.07	0.44	0.20
Mean dep. variable	30.82	30.82	30.82	30.82	30.81
Observations	22,696	22,696	22,696	22,494	22,628
Number of Individuals	11,348	11,348	11,348	11,247	11,314

Notes: Standard errors clustered at the municipality level. *** p<0.01, ** p<0.05, * p<0.1. All models control for individual characteristics and household characteristics and date of interview, wave, municipality, and individual fixed effects, as well as, the interaction of each of these controls with the relevant subgroup.

Table 5: Heterogenous impact of violent crime on risk aversion by changes in individual characteristics between MxFLS2 and MxFLS3

	Most risk averse = 100			
	(1)	(2)	(3)	(4)
Homicide rate	1.525***	1.460***	1.453**	1.175**
	[0.481]	[0.503]	[0.581]	[0.528]
Homicide Rate*I(Employment in MxFLS2=1 and in MxFLS3=0)		0.854		
		[0.797]		
Homicide Rate*I(Bottom Quartile of Change in PCE from MxFLS2 to MxFLS3)			0.533	
			[0.650]	
Homicide Rate*I(Scared of Being Attacked at Night in MxFLS2=0 and in MxFLS3=1)				1.356**
				[0.562]
P-value for F-Test (Homicide Rate + Homicide Rate Interaction=0):		0.00	0.00	0.00
Mean dep. variable	30.82	30.81	30.83	30.82
Observations	22,696	22,558	22,212	22,540
Number of Individuals	11,348	11,279	11,106	11,270

Notes: Standard errors clustered at the municipality level. *** p<0.01, ** p<0.05, * p<0.1. All models control for individual characteristics and household characteristics and date of interview, wave, municipality, and individual fixed effects, as well as, the interaction of each of these controls with the relevant subgroup.

Table A1: Relationship Between Most Risk Averse Measure in MxFLS2 and Subsequent Risky Behaviors

Dependent Variable: Most Risk Averse in MxFLS2=100

	All		Males	
Risky Behavior in MxFLS3	(1)	(2)	(3)	(4)
Cigarettes Smoked per Week	-0.017**	-0.013*	-0.030	-0.026
	[0.008]	[0.008]	[0.020]	[0.020]
Migration (At Least 1 Month)			-6.038***	-5.382**
			[2.101]	[2.142]
Self-Employment			-1.22	-0.36
			[1.426]	[1.426]
P-value for F-Test (Cigs per Week=Migration=Self-Employment=0):			0.01	0.04
Mean dep. variable	17.35	17.35	17.48	17.48
Observations	10,351	10,351	11,330	11,330
Municipality Fixed Effects	NO	YES	NO	YES

Notes: Robust standard errors provided in brackets *** p<0.01, ** p<0.05, * p<0.1.

All models control for individual characteristics, household characteristics, and date of interview.

Table A2: Summary statistics

	In MxFLS2		In MxFLS3	
	Mean	Std. Dev.	Mean	Std. Dev.
Individual characteristics				
Female	60.4%		60.4%	
Age (years)	39.7	14.0	43.9	14.0
Married or cohabits	70.2%		72.4%	
Number of children	2.5	2.4	2.7	2.4
Education (years)	7.2	4.5	7.3	4.7
Worked last week	53.5%		56.4%	
Self-employed	15.4%		17.8%	
Earnings (quartic root)	3.4	3.8	3.8	4.0
HH characteristics				
HH size	4.9	2.3	4.9	2.4
Number of children of other HH members	1.6	1.5	1.4	1.4
HH PCE (quartic root)	5.6	1.3	6.0	1.3
Location of residence characteristics				
Rural	43.6%		36.0%	
Observations	11,348		11,348	

Table A3: Risk attitude index transition matrix between MxFLS2 and MxFLS3

Risk index in MxFLS3	Risk index in MxFLS2							Total
	1	2	3	4	5	6	7	
1	820	136	243	938	212	51	194	2,594
2	170	25	38	203	45	12	38	531
3	432	67	102	456	82	28	92	1,259
4	676	86	181	693	135	29	155	1,955
5	1,180	163	268	1,261	244	60	328	3,504
6	207	37	55	250	46	9	59	663
7	258	43	58	315	64	18	86	842
Total	3,743	557	945	4,116	828	207	952	11,348

Table A4: Self-reported feelings of safety from crime and homicide rates

	At the time of MxFLS3		At the time of MxFLS2	
	Feel less safe than 5 years ago = 100	Feel scared of being attacked during the night = 100	Feel less safe than 5 years ago = 100	Feel scared of being attacked during the night = 100
	(1)	(2)	(3)	(4)
Homicide rate change from 2005 to 2009	2.030***	1.031***	-0.335	-0.30
	[0.558]	[0.270]	[0.379]	[0.368]
Mean of dep. Variable	34.58	22.11	25.76	19.81
Observations	11,288	11,288	11,330	11,330

Notes: Standard errors clustered at the municipality level. *** p<0.01, ** p<0.05, * p<0.1.

All models control for individual characteristics, household characteristics, and date of interview.

Table A5: Previous Municipal Trends and Levels of Characteristics' Relationship to Current Homicide Rate

	Municipal Homicide Rate (per 10,000)	
	Level in 2009	Change From 2005 to 2009
Municipality Characteristics	(1)	(2)
CENSUS: Change in Share of Households Between 2000-2005 with:		
Televisions	-5.83	-3.86
	(5.81)	(8.16)
Piped Water	-1.99	4.46
	(4.73)	(5.44)
Sewage System	1.17	-5.29
	(3.46)	(4.71)
Electricity	3.95	10.54
	(9.34)	(11.00)
CENSUS: Change in Share of 21-65 Year Olds Between 2000-2005 with:		
Less Than Primary Education	0.16	-17.71 *
	(8.83)	(10.10)
At Least High School Diploma	-14.81	-34.72 *
	(15.54)	(17.64)
Speak Indigenous Language	-4.50	-10.80
	(6.73)	(6.63)
CENSUS: Change Between 2000-2005 in Share of:		
Less Than 18 Year Olds	10.12	0.21
	(19.02)	(23.86)
18 to 65 Year Olds	5.66	-7.44
	(27.35)	(30.27)
CENSUS: Change Between 2000-2005 in:		
Average Educational Attainment	1.59	1.62
	(1.65)	(1.85)
MxFLS: Change in Share of Older than 18 Year Olds Between MxFLS1-MxFLS2:		
Married	-5.77	-7.73
	(6.63)	(7.23)
Employed Females	-1.78	0.75
	(4.57)	(4.87)
Employed Males	1.05	2.17
	(4.86)	(4.81)
Self-Employed Females	-1.02	-4.48
	(4.35)	(4.38)
Self-Employed Males	1.42	2.79
	(4.07)	(4.24)
Rural	1.62	2.02 *
	(1.09)	(1.14)
Have Relative in the U.S.	-2.27	-2.12
	(1.79)	(1.84)
Have Thoughts of Future Migration	-2.34	-0.38
	(3.17)	(3.38)
Have Fear in the Day	-1.73	-0.09
	(5.66)	(6.32)
Have Fear in the Night	-2.59	-3.86
	(5.59)	(5.79)
MxFLS: Change Between MxFLS1-MxFLS2 in:		
Average Household Size	0.15	0.09
	(0.70)	(0.71)
Log Hourly Earning of Females Older than 18 (Pesos)	0.35	0.08
	(0.45)	(0.47)
Log Hourly Earning of Males Older than 18 (Pesos)	0.78	0.38
	(0.68)	(0.67)
Log Household Per Capita Expenditure (Pesos)	0.68	0.93
	(1.02)	(1.18)
MxFLS: Change in Share of Localities Between MxFLS1-MxFLS2 with:		
Increased Domestic Violence	-0.13	-0.17
	(0.43)	(0.43)
Presence of Vandalism	0.54	0.36
	(0.38)	(0.43)
Presence of Police	0.15	0.08
	(0.41)	(0.45)
MxFLS: Change Between MxFLS1-MxFLS2 in Localities:		
Number of Primary Schools/100	-0.01	-0.24
	(0.33)	(0.29)
Number of Junior Highs/100	-0.55	-0.08
	(0.66)	(0.62)
Number of High Schools/100	0.25	0.04
	(0.93)	(0.84)
Rate of Poor Households	0.00	-0.01
	(0.01)	(0.01)
Observations	136	136
Mean of Dependent Variable	1.88	0.97
F test: Jointly 0; Prob>F	0.45	0.18

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors provided.

Table A6: Robustness checks on impact of violent crime on risk aversion

	Main Result from Table 3, Column 6	Including Local Economic Controls[1]	Excluding Northern Border States[2]
	(1)	(1)	(1)
Homicide rate	1.525***	1.213***	1.723***
	[0.481]	[0.455]	[0.580]
Mean dep. variable	30.82	30.82	30.82
Observations	22,696	22,696	17,822
Number of individuals	11,348	11,348	8,911
Individual Fixed Effects	YES	YES	YES
Municipality Fixed Effects	YES	YES	YES

Notes: Standard errors clustered at the municipality level. *** p<0.01, ** p<0.05, * p<0.1. All models control for individual characteristics and household characteristics and date of interview fixed effects. Wave fixed effects included when using multiple waves.

[1]Local economic condition controls include: Municipality-year level electricity use (kWh), manufacturing industry and retail sector characteristics (# of establishments,

[2]Respondents from Mexican northern border states in the MxFLS (Coahuila, Nuevo León, and Sonora) are dropped from the sample.

Table A7: Robustness Checks for Risk Aversion Measure

	Panel A. Most risk averse = 100		
	Alternative treatments of "gamble averse" response		
	Gamble averse classified as most risk averse = 100	Gamble averse classified as most risk averse = 0	Gamble averse excluded
	(1)	(2)	(3)
Homicide rate	1.525***	1.720***	1.789***
	[0.481]	[0.456]	[0.502]
Mean of dep. Variable	30.82	24.19	26.46
Observations	22,696	22,696	19,686
Number of individuals	11,348	11,348	9,843

	Panel B. Most risk averse = 100		
	Alternative classifications of "most risk averse"		
	Classification [1]	Classification [2]	Classification [3]
Homicide rate	1.525***	1.762***	1.051**
	[0.481]	[0.526]	[0.448]
Mean of dep. Variable	30.82	39.44	27.18
Observations	22,696	22,696	22,696
Number of individuals	11,348	11,348	11,348
	Classification [4]	Classification [5]	Classification [6]
Homicide rate	0.955**	1.674**	1.912**
	[0.414]	[0.795]	[0.853]
Mean of dep. Variable	26.26	48.96	57.57
Observations	22,696	22,696	22,696
Number of individuals	11,348	11,348	11,348

Notes: Standard errors clustered at the municipality level. *** p<0.01, ** p<0.05, * p<0.1. All models control for individual and household characteristics and date of interview, wave, municipality, and individual fixed effects.

Classification [1]: "Most risk averse" in 05: risk index ≥ 5 (risk premium ≥ $400)
"Most risk averse" in 09: risk index ≥ 5 (risk premium ≥ $1,000)

Classification [2]: "Most risk averse" in 05: risk index ≥ 5 (risk premium ≥ $400)
"Most risk averse" in 09: risk index ≥ 4 (risk premium ≥ $750)

Classification [3]: "Most risk averse" in 05: risk index ≥ 6 (risk premium ≥ $1,400)
"Most risk averse" in 09: risk index ≥ 5 (risk premium ≥ $1,000)

Classification [4]: "Most risk averse" in 05: risk index = 7 (risk premium ≥ $3,400)
"Most risk averse" in 09: risk index ≥ 5 (risk premium ≥ $1,000)

Classification [5]: "Most risk averse" in 05: risk index ≥ 4 (risk premium ≥ $250)
"Most risk averse" in 09: risk index ≥ 5 (risk premium ≥ $1,000)

Classification [6]: "Most risk averse" in 05: risk index ≥ 4 (risk premium ≥ $250)
"Most risk averse" in 09: risk index ≥ 4 (risk premium ≥ $750)

Table A8. Relationship Between Attrition and Homicide Rate

Dependent variable equals 100 if respondent was interviewed in MxFLS2 but not MxFLS3 and 0 if interviewed in MxFLS2 and MxFLS3

	(1)	(2)
Δ in Municipal Homicide Rate between 2009	-3.494	-0.542
	[6.419]	[8.201]
Δ Homicide Rate between 2009 & 2005 interacted with MxFLS2 characteristics:		
Female		-0.444
		[0.437]
Age		0.031
		[0.075]
Age Squared		-0.001
		[0.001]
Married or cohabits		-0.095
		[0.451]
Number of children		0.089
		[0.071]
Education (years)		0.026
		[0.046]
Worked last week		0.204
		[0.459]
Self-employed		-0.177
		[0.329]
Earnings (quartic root)		-0.065
		[0.054]
HH size		0.128
		[0.120]
Number of children of other HH members		-0.213
		[0.199]
HH PCE (quartic root)		-0.124
		[0.142]
Rural		-1.910
		[1.592]
Scared of being attacked at night		-0.253
		[0.430]
Mean dep. variable	20.69	20.69
Observations	14,274	14,274

Notes: Standard errors clustered at the municipality level. *** p<0.01, ** p<0.05, * p<0.1. All models control for individual characteristics, household characteristics, date of interview, and municipality fixed effects.