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 a key role in many decisions over the life-course, factors that affect those attitudes are not well understood. This study investigates how risk attitudes are affected by elevated levels of insecurity and uncertainty brought on by an unanticipated increase in violent crime. Using longitudinal survey data on Mexican individuals collected before and during the recent dramatic increase in drug-related violence driven by the Mexican war on drugs, we examine how attitudes towards risk are affected by local-area increases in crime. This study contributes to the current literature by pairing a plausibly exogenous change in conflict with models that account for individual- and location-specific time-invariant unobserved factors and shield the estimates from endogenous migration. Our findings indicate that a rise in local-area violent crime results in increased risk aversion. These results suggest that a violent environment may adversely affect the long-term wellbeing of the exposed population through unexpected channels such as investment behavior and occupation choice.

I. Introduction

Many important decisions in life involve some amount of uncertainty. Hence, attitudes people have towards risk influence their choices and ultimately their well-being. A growing interest in the empirical literature on this topic has led to the development and improvement of methods to elicit and measure these attitudes. The most established method is to ask individuals to choose between a set of gambles with different payoffs, in which options that offer a higher expected return also involve greater risk. Using these measures, researchers have confirmed the importance of risk attitudes empirically. The willingness to take risks has been associated with many relevant decisions people make under uncertainty: insurance acquisition, precautionary saving decisions, investment behavior, patterns of occupational choice and mobility (Barsky et al., 1997; Bellemare and Shearer, 2010; Charles and Hurst, 2003; Kan, 2003; Kimball et al., 2008; Lusardi, 1998).

Given that these attitudes have an influence on vital economic decisions, it is important for researchers and policy makers to know whether risk attitudes change depending on the individual's circumstances. Various viewpoints throughout the social sciences have suggested that attitudes are determined by a multitude of factors (cultural, environmental, personal) and that large temporary shocks may be able to alter them permanently (Carmil and Breznitz, 1991; Tedeschi and Calhoun, 2004).

In line with this view, a literature has emerged that examines whether risk attitudes are responsive to major changes in the 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. at., 2013; Hanaoka et al., 2015; Malmendier and Nagel, 2011; Voors et. al., 2012). Establishing a causal relationship, though, presents several challenges. Since differential exposure can be correlated with pre-existing characteristics of the locality and risk attitudes may play a role in geographic sorting, it is likely that a non-causal association exists between exposure and willingness to take risks. Another threat to identifying a causal relationship is generated by potential behavioral responses to the change in the environment. One likely response to a significant localized shock is migration. If migration is selective and the analytical sample is based on the population distribution after the change has occurred, then exposure may be correlated with individual characteristics, including risk aversion. This study takes on these challenges to identification in an effort to contribute to the understanding of how flexible risk attitudes are to changes in the local environment. Specifically, we investigate the impact of the recent and unprecedented rise in violent crime in Mexico on attitudes towards risk.

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. The subsequent rise in crime occurred rapidly, and diffused widely throughout the country, affecting many regions that had previously had no exposure to the war on drugs, creating geographic heterogeneity that was uncorrelated with previous trends in any local characteristics (Brown, 2014; Velasquez, 2014). There are several potential mechanisms through which this unanticipated violence outbreak may have an impact on risk attitudes. First, given the magnitude of the outbreak, the increasing brutality of the crimes, and the heightened visibility of the violence due to press coverage and the active promotion by drug cartels through narco-messages, Mexicans living near the violence are expected to be psychologically exposed[1]. Psychological exposure may affect the perception people have of the riskiness of the environment and the way they behave when faced with other risks. Second, 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, 2011; Robles et. al., 2013, Velásquez, 2014).

To explore this research question, we rely on the Mexican Family Life Survey (MxFLS), an extremely rich longitudinal dataset. This dataset is ideally suited for our purposes and allows us to rigorously address the serious threats to identification common in this type of study. The MxFLS is representative of the Mexican population living in Mexico in 2002, when the baseline survey was conducted. In the two follow-ups of the survey, respondents' attitudes towards risk were elicited using the most established method to ask individuals to choose between gambles with different payoffs[2]. Key for our study, the follow-ups span periods before and after the rise in violence. The strict follow-up policy adopted by the MxFLS is also crucial, as all baseline respondents were sought for re-interview in both follow-ups, independent of whether they had migrated within Mexico or to the United States.

By pairing the MxFLS with the municipality and month level homicide data collected by the National Institute of Statistics and Geography (INEGI, its Spanish acronym), we are able to compare attitudes towards risk of the same individual both before and after the outbreak of violence. This is a major contribution to the literature as it allows us to implement an individual fixed effect strategy and control for all time-invariant

[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.

[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.

heterogeneity that may be correlated with exposure to violence and risk attitudes. Another contribution of this study is that we provide evidence that migration was a behavioral response to violent crime in Mexico and our empirical approach is designed to remove contamination from this systematic migration.

Our results show that higher levels of violence increase risk aversion. In particular, 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. Further, exploiting the richness of the MxFLS, we find that violence had a greater effect on the risk aversion of self-employed women. This is consistent with the evidence that the economic outcomes of self-employed individuals were the most sensitive to local conflict exposure (Velásquez, 2014). We also find suggestive evidence that the risk attitudes of individuals with lower emotional well-being were particularly vulnerable to the rise of violent crime.

II. Background

Since 2008, Mexico has suffered a staggering rise in crime. Figure 1 shows the trend in the monthly homicide rate from the mid-nineties until 2011 (red solid line). The modest declining trend up to 2007 is followed by a dramatic increase, with the homicide rate almost tripling between 2007 and 2011(from .9 homicides per 10,000 habitants in 2007 to 2.4 in 2011). Due to its geographic location, Mexico has long played a major role in the flow of drugs between Latin America and the United States and, as is evident from the figure, most of the increasing trend is explained by drug-related violence (green dashed line). While the drug trade has been active in Mexico for many years, it is believed that one of the main contributors to the recent outbreak of violence is a change in the military approach to drug trafficking organizations introduced by Felipe Calderón's government.

In contrast to previous tactics, Calderón's strategy 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 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). Calderón's approach bore early success as cartel leaders were jailed, killed, or on the run and, even one year after the military strategy was already in place, violence remained stable. It was not until 2008 that the first considerable increase in crime occurred as a result of an untended consequence of the new war on drugs. As Calderón's troops successfully displaced the leaders of the OCGs, the cartels, having lost their leadership, began to fracture and fight amongst themselves for control of the local drug trade. Overall, the number of cartels operating in Mexico grew from six in 2006 to sixteen by 2011. Once the outbreak happened, violence not only escalated, but also spread across the country, reaching areas that previously had no strategic value for drug-trafficking and were thus unaffected by the cartels (Guerrero and Gutiérrez, 2011).

The spread of violence suffered in Mexico is shown in the maps contained in Figure 2. These maps show the municipality homicide rates per 10,000 inhabitants for 2002, 2005, 2007 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. As mentioned, throughout 2007, the first year Calderón's strategy was implemented, violence was stable. 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 also changed. Given the increased competition between OCGs, these organizations sought to build a reputation by committing and actively advertising increasingly brutal crimes (Beittel, 2013; Guerrero and Gutiérrez, 2011; Molzán et. al., 2012). Also, they sought to diversify their financial sources and turned to crimes that directly affected the civil population, such as extortions, kidnappings and car thefts. Even executions became more frequently targeted at civilians, particularly at authorities, reporters, and those not paying transit or extortion fees. In consequence, drug-related violence became embedded in society and triggered fear among the population (Díaz-Cayeros et. al., 2011).

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

There are several channels through which we may expect the high-crime environment created by the Mexican drug war to affect people's levels of risk aversion. First, given the magnitude of the outbreak of violence and the increasing brutality of crimes, together with the heightened media coverage, psychological exposure is expected. 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. On the other hand, psychological evidence of diminishing sensitivity suggest that 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, 2011; Robles et. al., 2013, Velásquez, 2014). 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 who have also seen their per capita household expenditure diminished. 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.

The empirical literature on the causal effect of violent conflict on attitudes towards risk is still scarce. Voors et. al. (2012) is one of the few exceptions. The authors study the impact of a civil war in Burundi on social, risk, and intertemporal choices. From 1993 to 2005 Burundi suffered a civil war between the two main ethnic groups. The authors find that individuals exposed to violence exhibit greater risk-seeking behavior six years after the end of the civil war.

Another study on this topic is Callen et. al.'s work, which explores the impact on risk attitudes of the violence that ravaged Afghanistan for nearly thirty years. The violence escalated in the country after the bloody seizure of power by the People's Democratic Party of Afghanistan. Unlike Voors et. al. the authors do not find a 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 only among those who were exposed to violence. Interestingly, the authors find that risk tolerance under uncertainty increases but that certainty is preferred when available.

A common limitation to both studies is that they need to rely on information collected after the change in the conflict environment. Thus they can only exploit geographical variation in the levels of violence and are unable to examine behavioral responses (e.g. migration) to the conflict. If the geographical variation in violence is endogenous to omitted factors that are correlated with risk aversion or the behavioral responses are systematically related to both violence exposure and risk attitudes, the results would be biased. This misidentification might be generated if, for example, individuals with higher levels of risk aversion are more likely to move away from areas suffering an increase in crime. Our study aims to contribute to this literature by directly addressing these concerns through the use of a unique dataset collected on a population exposed to a plausibly exogenous change in the violence environment.

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), an extremely 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, its Spanish acronym) 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, both datasets cover periods 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[3], 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 reinterview, 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 panel respondents were recontacted 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 V and find no evidence that this potential issue is biasing our results.

The fact that the MxFLS followed migrants is crucial for the examination of whether systematic migration is a behavioral response to violence. In section V, we find evidence of endogenous migration of individuals with characteristics that are likely correlated with risk attitudes. If migrants had not been followed, we would have systematically lost these individuals, and we would have been left with a selected sample. Given this result, as will be discussed in section V, we choose an empirical specification that shields our estimates from the bias of endogenous migration.

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.

[3] Only 6% of the sample of panel respondents interviewed in Mexico was interviewed after 2010.

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 1A in the Appendix, 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 a sure amount of \$1,000 and an alternative of receiving either \$500 or \$2,000 with equal probability (in Mexico, the symbol \$ stands for pesos[4]). The idea behind this choice set is that a more risk averse individual would prefer the sure amount even though the gamble has higher expected payoff. 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.

MxFLS3 contains the same type of questions, but the amounts and the progression changed with the aim of making the process simpler and increasing understanding. Figure 2A 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.

In Tables A1 and A2 in the Appendix we describe the “gamble averse” individuals. In Table A1 we can see that their choices on the hypothetical questions in MxFLS2 are distributed similarly to those of other respondents. In Table A2, the goal is to evaluate whether “gamble averse” individuals are similar to “most risk averse” individuals by looking at how they compare to the rest of the respondents in a set of characteristics. To do this we have four groups that we compare to the rest of the respondents: the most

[4] At the time of MxFLS2, \$ 1,000 was around US\$ 90 and represented approximately 80% of the minimum monthly wage.

extreme type of "gamble averse", that is, those who prefer the sure amount even when the gamble offers strictly greater amounts in any case (column 1), all "gamble averse" individuals (column 2), "gamble averse" and "most risk averse" individuals (column 3) and "most risk averse" individuals excluding "gamble averse" from the sample (column 4). Results suggest that these four groups are different from the rest of the sample in similar ways. Nevertheless, it seems that the "gamble averse" are not exactly like the "most risk averse" individuals, as they have higher levels of education and are more likely to have a job. Given these findings, we take a skeptical approach to the classification of the "gamble averse". In section VII, we show that our results are robust to different classifications of this group.

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 couple more questions. The risk aversion index according to the choices is shown at the bottom of Figure 2A.

As these 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, we next describe our preferred classification. 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 (gamble averse individuals are included in this category as well in the main results of the paper). Individuals in this category have a risk premium greater than $1,000. Due to the fact that properly defining these classifications is not straightforward, in section VII we confirm the robustness of our results to different classifications of "most risk averse".

Our analytical sample includes those individuals interviewed at baseline who were 15 years old or older at the time of that interview and answered the hypothetical questions aimed at measuring risk aversion in both MxFLS2 and MxFLS3[5]. Table 1 shows the distribution of the risk aversion indexes in both waves for our analytical sample. According to our preferred classification, 17% of our sample is most risk averse in MxFLS2 and 44% in MxFLS3. For this classification, Table 2 shows the distribution of being most risk averse in MxFLS3 given the category of the individual in MxFLS2. Changing categories between MxFLS2 and MxFLS3 is very frequent. This can be partly attributed to noise and partly to other factors and risk attitudes that have changed over the four years period between measurements. Our goal is to establish whether the extraordinary 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. As we have previously seen, total homicides follow the same trend as drug-related homicides. 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 A3 of the Appendix, columns 1-3))[6].

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

[5] 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.

[6] 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.

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 (Molzán et. al., 2012).

We next explore the relationship between individuals' risk aversion and the level of violence to which they are exposed. The exposure to violence an individual is assigned is the homicide rate in his/her municipality of residence over the 12 months prior to the MxFLS interview. The analysis is conducted on MxFLS2 and MxFLS3 separately, mimicking an approach where only cross-sectional data is available. The results, presented in Table 3, show that less risk averse individuals were living in municipalities with higher violence during MxFLS2, but there is no significant association between risk aversion and levels of violence for MxFLS3. Once municipality fixed effects are added, there is no significant association for either wave. The main concern with this analysis is that the estimates might be capturing not only the effect of violence but also the heterogeneity of people exposed to different levels of crime. Our identification strategy addresses this issue 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. Another major concern with the analysis is that the estimates may be biased due to endogenous migration. This is a concern that we are also able to address.

V. Identification strategy

V.1. Selective attrition, exogeneity and behavioral responses

Despite MxFLS' successfully low levels of attrition, it is important to evaluate whether selection in our analytical sample is correlated 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. Our analytical sample includes those individuals who were interviewed in baseline and who answered the hypothetical questions aimed at measuring risk aversion in both MxFLS2 and MxFLS3. To test for potential selection bias from attrition we estimate the following linear probability model for all individuals aged 15 or older at baseline who were interviewed in MxFLS2:

$$A_{ij} = \alpha_0 + \alpha_1 \Delta Hom_j + \alpha_2 X_{ij} + \beta(X_{ij} \times \Delta Hom_j) + \varepsilon_{ij} \tag{1}$$

where A_{ij} is a binary variable equal to 1 if individual *i*, living in municipality *j* at the time of the MxFLS2 interview, did not answered the risk aversion questions in MxFLS2 or MxFLS3, ΔHom_j is the change in the homicide rate between 2005 and 2009 in municipality *j*, and 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. When unning this regression excluding the interacted terms, α_1, provides evidence on whether overall attrition is related to the change in violence. More importantly to the representativeness of our results, we evaluate whether conflict related attrition was systematically different for individuals with certain characteristics. Evidence on this is provided by the set of coefficients represented by β in equation 1. Results are reported in Panel A of Table 4. We do not find evidence that attrition is on average correlated with the change in violence (column 1), and the complete model including interaction terms (column 2) shows that the only interaction with gender is statistically significant, indicating that men are more likely to attrite when violence increases. This finding suggests that any correlation between gender and risk attitudes would bias our results. Hence, we will probe the robustness of our main results when the sample is stratified by gender. In columns 3 to 6 of Table 4, we show that attrition is not correlated with violence in these subsamples.

A first order concern when trying to establish causality between violent crime and attitudes is endogenous migration. Systematic migration can occur as a behavioral response to crime and failing to account for it can lead to biased results. For instance, if individuals that exhibit greater risk aversion are more likely to move away from municipalities with high levels of violence and migration is ignored, the impact of crime on risk aversion would be downward biased. To examine whether migration responded to the change in the conflict environment we estimate a regression with the same empirical specification as the model for sample selection in equation (1), but using a measure of migration as the dependent variable. Our measure of migration is a binary variable equal to 1 if the respondent was interviewed in a different municipality in MxFLS2 and MxFLS3 or if he or she reported a long-term migration (at least one year) outside the municipality of residence in MxFLS2. Panel B of Table 4 presents the results for our analytical sample. We find evidence of selective migration. Respondents living in rural areas are more likely to migrate when violence increases. This result holds when we restrict the sample to women, but disappears when we restrict the sample to men. Nonetheless, unemployed men and higher income men are more likely to migrate when crime rises. If the follow-up policy of the MxFLS had excluded migrants, sample selection would likely bias our estimates. This analysis highlights the importance of accounting for endogenous migration and as such we deal with this issue directly in our identification strategy.

Another potential concern is whether the geographic heterogeneity in conflict is correlated with other aspects of the municipalities. If violence patterns actually reflect underlying trends in other municipality characteristics, we would not be able to distinguish the impact of violence from the impact of those other trends on people's levels of risk aversion. This is an unlikely scenario given the suddenness and political origins of the outbreak of violence. Nonetheless, we formally explore this concern by looking at whether violence heterogeneity is correlated with previous trends in municipality characteristics. The set of municipal trends used is quite rich as it includes demographics, socioeconomic characteristics, educational attainment and infrastructure, employment status and earnings of men and women, migration expectations, having relatives in the United States and variables related to crime in the municipality. Some of these trends are constructed using IPUMS samples of the 2000 and 2005 Mexican census and some are constructed using the MxFLS1 and MxFLS2 waves[7]. Table 5 presents the results for the municipal homicide rate in 2009 (column 1) and for the change in this rate between 2005 and 2009 (column 2). The findings from this analysis strongly suggest that previous municipal trends do not predict future violence[8].

Moreover, evidence supporting the idea that the change in the conflict environment was unanticipated and unrelated to prior trends in crime/insecurity can be provided using the MxFLS data on self-reported feelings of safety. Estimating models at the individual level, we find no correlation between feeling less safe or more scared of being attacked in MxFLS2 and subsequent changes in homicide rates between 2005 and 2009 (see Table A3 of the Appendix, columns 4-6). This suggests that municipalities that would subsequently be exposed to larger increases in violence were not already on a downward trend in safety and insecurity..

One additional potential concern is that the Great Recession, which started between the MxFLS2 and MxFLS3 waves, is a confounder for crime exposure. If crime trends varied with economic downturn at the municipality level, then we would not be able to separately identify the effect of crime. The analysis in Table 5 suggests that this is unlikely as previous municipal trends related to economic activity (such as employment status and earnings) proved to be unrelated to future violence. In addition, other studies that have looked at this issue specifically confirm that the geographic heterogeneity of crime in Mexico does not correspond to the differential regional magnitude of the Great Recession (Ajzenman et al., 2014; Velásquez, 2014).

V.2. Empirical specification

The identification strategy we will use to estimate the impact of violent crime on attitudes towards risk will address the concerns discussed in the previous section. First, in order to shield our estimates from the bias of endogenous migration, we follow an intent-to-treat approach. 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.

[7] Since we use MxFLS1 information we need to restrict the sample to the MxFLS1 municipalities.
[8] Only a few of the extensive set of covariates is statistically significant (at the 10% level). This is less than what would be expected by chance and they are jointly not significant.

It is important to mention that 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 .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 temporal and spatial variation to identify the effect of exposure to violent crime on people's levels of risk aversion.

Even though we found no evidence that violence responded to previous trends in municipality characteristics, in an attempt to limit the possibility that time-varying characteristics 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 and thus unaffected by current levels of crime. We further include year and month of interview fixed effects to control for temporal and seasonal unobserved heterogeneity.

To further avoid potential omitted variable bias, we exploit the panel nature of our survey and compare risk attitudes of the same individuals before and after the change in the conflict environment by implementing an individual fixed-effects strategy. This approach allows us to control for all unobserved time-invariant heterogeneity. If municipalities that experienced relatively larger increases in crime contained a greater proportion of individuals with certain characteristics, as long as those characteristics are fixed over time, they will be accounted for in our model. This will also help us to control for more subtle sources of potential bias. For instance, under the possible scenario that more risk averse individuals are harder to convince to be interviewed and thus are interviewed at a later date in a plausibly higher crime environment, a non-causal link between higher crime and greater risk aversion would be captured if individual fixed-effects were not included.

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

$$Y_{ijt} = \beta_1 Hom_{jt} + \beta_2 X_{it} + \theta_i + \gamma_t + \varepsilon_{ijt}, \qquad (2)$$

where Y_{ijt} is a binary variable equal to 1 if individual *i*, living in municipality *j* at the time of the MxFLS2 interview 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 previously mentioned time-varying characteristics measured during the previous wave, θ_i captures individual fixed effects and γ_t

captures time of interview fixed effects, including a wave fixed effect and year and month of interview fixed effects.

VI. Results

VI.1. General Results

Our empirical strategy addresses common and serious threats to the identification of the impact of local violence on attitudes towards risk. Results are shown in Table 6. The estimates build up to equation 2 in column (4). In column (1), without controlling for time and municipality fixed effects, we find no effect of violence on risk aversion. Results are similar once we add time fixed effects in column (2). In sharp contrast, a precisely estimated positive effect is found once municipality fixed effects are included in column (3). The main gain of this specification is that it allows us to compare similar individuals, similar in that they live in the same municipality, under low and high levels of violence. In column (4), our preferred specification, we go further and use individual fixed effects to compare the same individual under different levels of crime. This is our main result and it indicates that violence increased people's risk aversion. A rise 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.

VI.2. Heterogeneous Effects

As previously described, the change in the conflict environment was not homogeneous across Mexico. It is well-documented that the Mexican drug war is a more urban phenomenon. Most of the cartels profits are generated by drug-trafficking activities rather than by drug production; thus drug cartels are mainly interested in controlling urban warehouses and highway transportation routes (Castillo et. al., 2013; Llorente et. al., 2014). Accordingly, crime growth was greater in more urban municipalities (Velásquez, 2014). It is thus possible that the type and severity of the crimes also differ between rural and urban areas. For example, it could be the case that, even at the same homicide rate level, more extortions or kidnappings take place in urban areas, or the homicides in urban areas may be more violent. To evaluate whether the results vary between these areas, we stratify the sample by the urban/rural status of the municipality of residence in MxFLS2.

Another useful stratification is by gender. 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 psychological reaction to a rise of violence might differ between men and women. Panel A of Table 7 shows our results for each of these stratifications. Consistent with urban areas being more severely exposed to crime, we find that results are more precisely estimated for those areas. Differences are not statistically significant though. We also find that results for men and women are very similar.

Exploiting the richness of the MxFLS dataset further, we examine whether crime exposure had heterogeneous effects on risk aversion based on an individual's characteristics[9]. To do this we modify our main specification in equation (2) by interacting every covariate with binary variables which capture a particular individual's characteristic. The first factor we explore is economic resources. One might think that having greater resources can help individuals avoid crime by allowing them to afford better transportation or security at work. Using household per capita expenditure and years of education as measures of resources, we do not find evidence that this insulates them from the effects of crime on attitudes towards risk. Results reported in Panel B show that there is no statistical significant difference in the impact of violence according to the level of resources. Nonetheless, we find that, in general, estimates are more precise for those with higher household per capita expenditure and for those with more years of education[10]. One potential explanation for this result is that wealthier and more educated individuals understand the hypothetical questions aimed at eliciting attitudes towards risk better and thus their measures of risk aversion are less noisy.

We also explore whether individuals were more affected depending on their employment status. Consistent with anecdotal evidence on business owners being particularly affected by violent crime, Velásquez (2014) finds that exposure to violence reduced labor participation of self-employed women. Accordingly, we find, in Panel C, that violence had a greater effect on risk aversion for self-employed rural women. This is the only difference that is statistical significant.

Finally, we examined whether an individual's emotional well-being made them more or less vulnerable to crime's impact on risk attitudes. In order to do this we use a set of questions included in the MxFLS aimed at measuring depression. A widely used measure of mental well-being is the one based on the Short Form 36 (SF-36) Health Survey (Adams and Boscarino, 2005; Cornaglia et. al., 2013; Guite et. al., 2009). We construct a proxy of this measure using the questions asked in MxFLS that are closest to the ones used in the SF-36 index and adapting the same scoring system. Then we classify respondents in two groups: the ones who got the highest possible score and those that did not. The results of our model interacted with these

[9] These characteristics are measured at the time of MxFLS2 so that they are not affected by the change in violence.
[10] The exception is urban women, for whom estimates are more precise for those at the bottom 50^{th} percentile of household per capita expenditure.

variables are shown in Panel D. Differences are not statistically significant, but we find suggestive evidence that those with lower emotional well-being were more strongly affected by crime.

VII. Robustness checks

In this section we report the outcomes of two important robustness checks. In our main results we include the "gamble averse" individuals in the "most risk averse" category. In this section we explore 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. Results, shown in Panel A of Table A4 in the Appendix, confirm that our estimate of the impact of violence on risk aversion is robust to these two alternative approaches.

The second robustness analysis 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 Table A4.[11] The robustness of our estimate to these alternative classifications is also confirmed.

VIII. Conclusion

There is a growing interest in understanding whether an individual's attitudes towards risk respond to major changes in their environment. To answer this question rigorously a number of serious challenges need to be overcome. Our study on the impact of the Mexican drug war on risk attitudes contributes to the literature by addressing important threats to identification. Making use of a unique dataset, we implement an identification strategy that accounts for endogenous migration and controls for all time-invariant heterogeneity that may be correlated with exposure to violence and risk attitudes. We also provide evidence that we are capturing the impact of violence and not some other unobserved municipal trend and that our estimates are not biased due to selective attrition.

We find that exposure to violence increases risk aversion. The effect is largest for self-employed rural women. This is consistent with the evidence that the economic outcomes of self-employed individuals in Mexico were more adversely impacted by the surge in crime (Velásquez, 2014). We also find suggestive evidence that the risk attitudes of individuals with lower emotional well-being are more responsive to conflict exposure.

[11] In each specification the "gamble averse" individuals are included in the "most risk averse" category.

Our results extend the current understanding of the reach violent conflict has 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 has another pathway through which it can impact the long-term economic wellbeing of the exposed.

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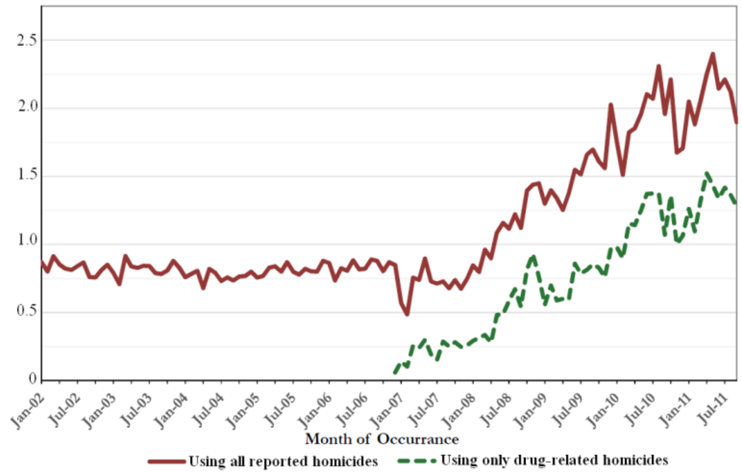
TABLES AND FIGURES

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



Notes: Data on all reported homicides are collected by the National Institute of Statistics and Geography (INEGI, its Spanish acronym). Data on drug-reported homicides are collected by the National Public Security System (SNSP, its Spanish acronym).

Figure 2: Municipality Homicide Rates per 10,000 Inhabitants

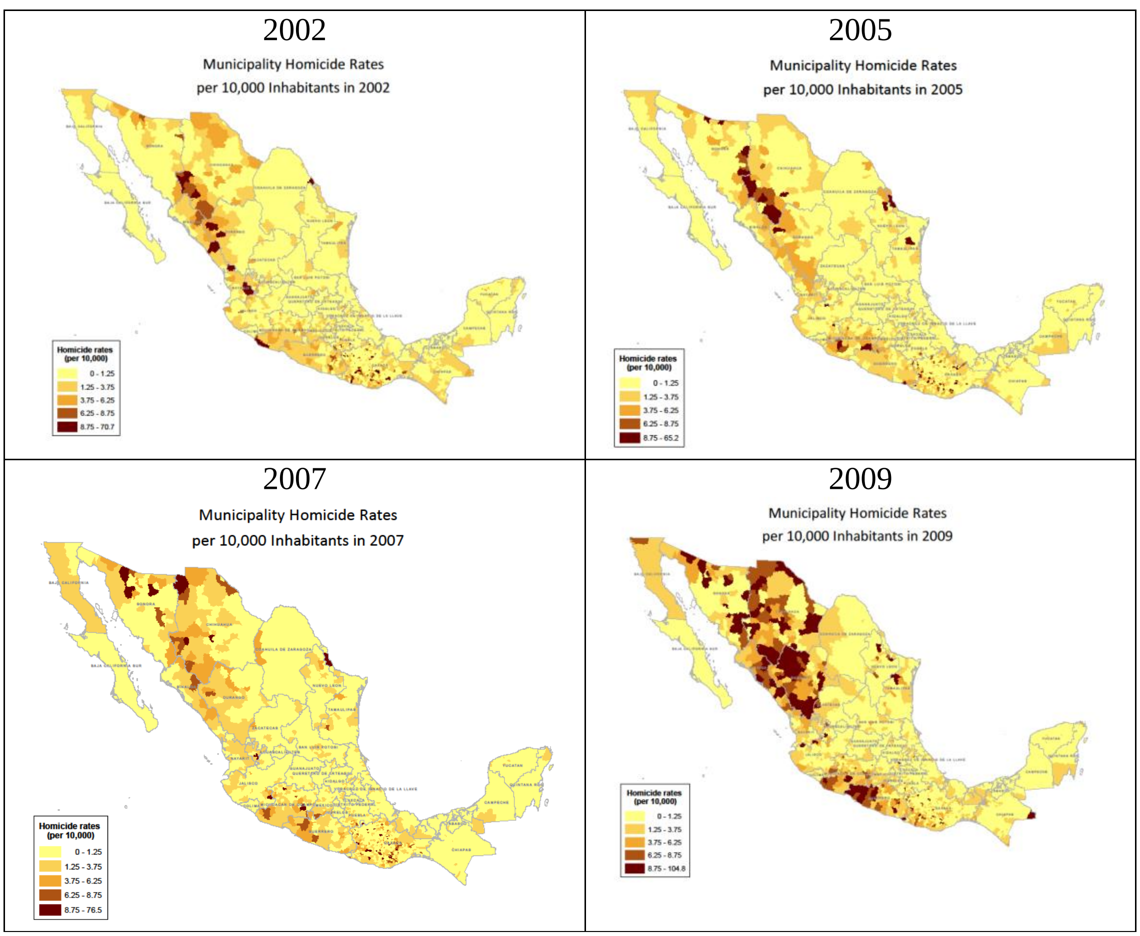


Table 1: Distribution of risk aversion indexes

MxFLS2		MxFLS3	
1	33.0%	1	22.9%
2	4.9%	2	4.7%
3	8.3%	3	11.1%
4	36.3%	4	17.2%
5	7.3%	5	30.9%
6	1.8%	Gamble averse	5.8%
7	8.4%	Gamble averse-pay	7.4 %
Observations	11,348	Total	11,348

Table 2: Most risk averse in MxFLS3 given category in MxFLS2

Most risk averse in MxFLS3	Most risk averse in MxFLS2		Total
	No	Yes	
No	5,266	1,073	6,339
	56%	54%	56%
Yes	4,095	914	5,009
	44%	46%	44%
Total	9,361	1,987	11,348

Table 3: Correlation between risk aversion and violent crime

	MxFLS2 Most risk averse = 100			MxFLS3 Most risk averse = 100		
	[1]	[2]	[3]	[1]	[2]	[3]
Homicide rate	-2.07**	-2.19***	-0.36	0.29	0.37	-0.16
	(0.82)	(0.77)	(1.11)	(0.33)	(0.33)	(0.56)
Mean dep. variable	17.51	17.51	17.51	44.13	44.13	44.14
Observations	11,348	11,348	11,348	11,348	11,348	11,348
Time FE	-	YES	YES	-	YES	YES
Municipality FE	-	-	YES	-	-	YES

Notes: Standard errors clustered at the municipality level. *** p<0.01, ** p<0.05, * p<0.1.
In all models we further control for time-varying covariates from the previous MxFLS wave.

Table 4: Attrition and Migration

	Panel A. Attrition = 100						*Panel B. Migration = 100*					
	All		Women		Men		All		Women		Men	
	[1]	[2]	[3]	[4]	[5]	[6]	[1]	[2]	[3]	[4]	[5]	[6]
Δ Hom. rate 09 - 05	0.21	0.07	0.05	-1.42	0.40	1.19	0.08	-0.76	0.14	-0.12	-0.06	-0.74
	(0.22)	(2.13)	(0.23)	(2.48)	(0.33)	(3.13)	(0.19)	(1.53)	(0.22)	(1.91)	(0.20)	(1.80)
Δ Hom. rate 09 - 05 *interacted with:*												
Female		-0.78**						0.31				
		(0.34)						(0.32)				
Age		0.09		0.09		0.04		-0.03		-0.06		0.03
		(0.06)		(0.08)		(0.10)		(0.04)		(0.06)		(0.08)
Age squared		-0.00*		-0.00		-0.00		0.00		0.00		-0.00
		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
Married		-0.46		-0.58		-0.18		-0.50*		-0.63		-0.25
		(0.34)		(0.53)		(0.46)		(0.28)		(0.38)		(0.39)
Years of education		0.05		0.06		0.07		0.04		0.05		0.03
		(0.05)		(0.06)		(0.07)		(0.04)		(0.04)		(0.05)
Has a job		-0.43		-0.09		-0.43		-0.19		0.44		-1.15***
		(0.57)		(0.86)		(0.98)		(0.33)		(0.63)		(0.40)
Earnings (quartic root)		-0.04		-0.10		-0.01		0.07*		-0.03		0.12**
		(0.06)		(0.10)		(0.08)		(0.04)		(0.10)		(0.05)
HH size		0.05		0.04		0.06		0.01		0.00		0.01
		(0.05)		(0.06)		(0.11)		(0.03)		(0.03)		(0.07)
HH PCE (quartic root)		-0.13		-0.08		-0.17		0.08		0.13		-0.02
		(0.11)		(0.14)		(0.18)		(0.12)		(0.13)		(0.18)
Reside in rural locality		0.28		-0.03		0.57		1.32**		1.60***		0.99*
		(0.50)		(0.47)		(0.70)		(0.52)		(0.54)		(0.54)
Mean of dep. Variable	32.03	32.03	24.11	24.11	41.43	41.43	8.38	8.38	8.72	8.72	7.83	7.83
Number of observations	17,258	17,258	9,372	9,372	7,886	7,886	11,123	11,123	6,859	6,859	4,264	4,264

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

All characteristics interacted are measured at the time of MxFLS2. Includes the same characteristics are further controls.

Table 5: Correlation between homicide rates and previous municipal trends

	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	-6.73	-5.33
	(6.13)	(7.76)
Piped Water	-1.59	4.53
	(5.01)	(5.59)
Sewage System	1.52	-4.62
	(3.74)	(4.44)
Electricity	1.60	7.97
	(9.81)	(11.05)
CENSUS: Change in Share of 21-65 Year Olds Between 2000-2005 with:		
Less Than Primary Education	-0.15	-18.64*
	(8.27)	(9.97)
At Least High School Diploma	-11.19	-29.55*
	(13.40)	(15.20)
Speak Indigenous Language	-3.47	-10.25
	(6.91)	(6.76)
Illiterate	-13.38	-22.81
	(27.76)	(31.62)
CENSUS: Change Between 2000-2005 in Share of:		
Less Than 18 Year Olds	7.83	-3.16
	(18.72)	(22.58)
18 to 65 Year Olds	3.79	-10.17
	(27.07)	(29.57)
CENSUS: Change Between 2000-2005 in:		
Average Educational Attainment	1.12	1.02
	(1.46)	(1.61)
MxFLS: Change in Share of Older than 18 Year Olds Between MxFLS1-MxFLS2:		
Married	-4.43	-6.36
	(6.12)	(6.77)
Employed Females	-0.88	1.31
	(4.40)	(4.64)
Employed Males	0.27	1.46
	(4.69)	(4.63)
Self-Employed Females	-2.42	-5.18
	(4.66)	(4.73)
Self-Employed Males	2.89	4.20
	(3.76)	(3.98)
Rural	1.63	2.07*
	(1.02)	(1.10)

(Continued)

Table 5: Correlation between homicide rates and previous municipal trends *(Continued)*

Have Relative in the U.S.	-2.96*	-2.73
	(1.64)	(1.68)
Have Thoughts of Future Migration	-2.15	-0.12
	(3.34)	(3.55)
Feel scared of being attacked during the day	-1.15	0.41
	(6.39)	(6.95)
Feel scared of being attacked during the night	-4.70	-6.23
	(6.44)	(6.69)
MxFLS: Change Between MxFLS1-MxFLS2 in:		
Average Household Size	0.03	-0.10
	(0.68)	(0.69)
Log Hourly Earning of Females Older than 18 (Pesos)	0.29	-0.01
	(0.46)	(0.48)
Log Hourly Earning of Males Older than 18 (Pesos)	0.78	0.35
	(0.71)	(0.70)
Log Household Per Capita Expenditure (Pesos)	0.86	1.16
	(1.05)	(1.22)
MxFLS: Change in Share of Localities Between MxFLS1-MxFLS2 with:		
Increased Domestic Violence	-0.05	-0.13
	(0.44)	(0.44)
Presence of Vandalism	0.50	0.35
	(0.38)	(0.43)
Presence of Police	0.19	0.13
	(0.40)	(0.43)
MxFLS: Change Between MxFLS1-MxFLS2 in Localities:		
Number of Primary Schools	0.00	0.00
	(0.00)	(0.00)
Number of Junior Highs	-0.01	0.00
	(0.01)	(0.01)
Number of High Schools	0.01	0.00
	(0.01)	(0.01)
Rate of Poor Households	0.00	-0.01
	(0.01)	(0.01)
Observations	135	135
Mean of Dependent Variable	1.89	0.97
F test: Jointly 0; Prob>F	0.20	0.23

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

Table 6: Impact of violent crime on risk aversion

	Pooling MxFLS2 and MxFLS3 Most risk averse = 100			
	[1]	[2]	[3]	[4]
Homicide rate	-0.03	0.03	1.25***	1.49***
	(0.28)	(0.29)	(0.40)	(0.47)
Mean dep. variable	30.82	30.82	30.82	30.82
Observations	22,696	22,696	22,696	22,696
Number of individuals	11,348	11,348	11,348	11,348
Time FE	-	YES	YES	YES
Municipality FE	-	-	YES	-
Individual FE	-	-	-	YES

Notes: Standard errors clustered at the municipality level. *** p<0.01, ** p<0.05, * p<0.1.
In all models we further control for time-varying covariates from the previous MxFLS wave.

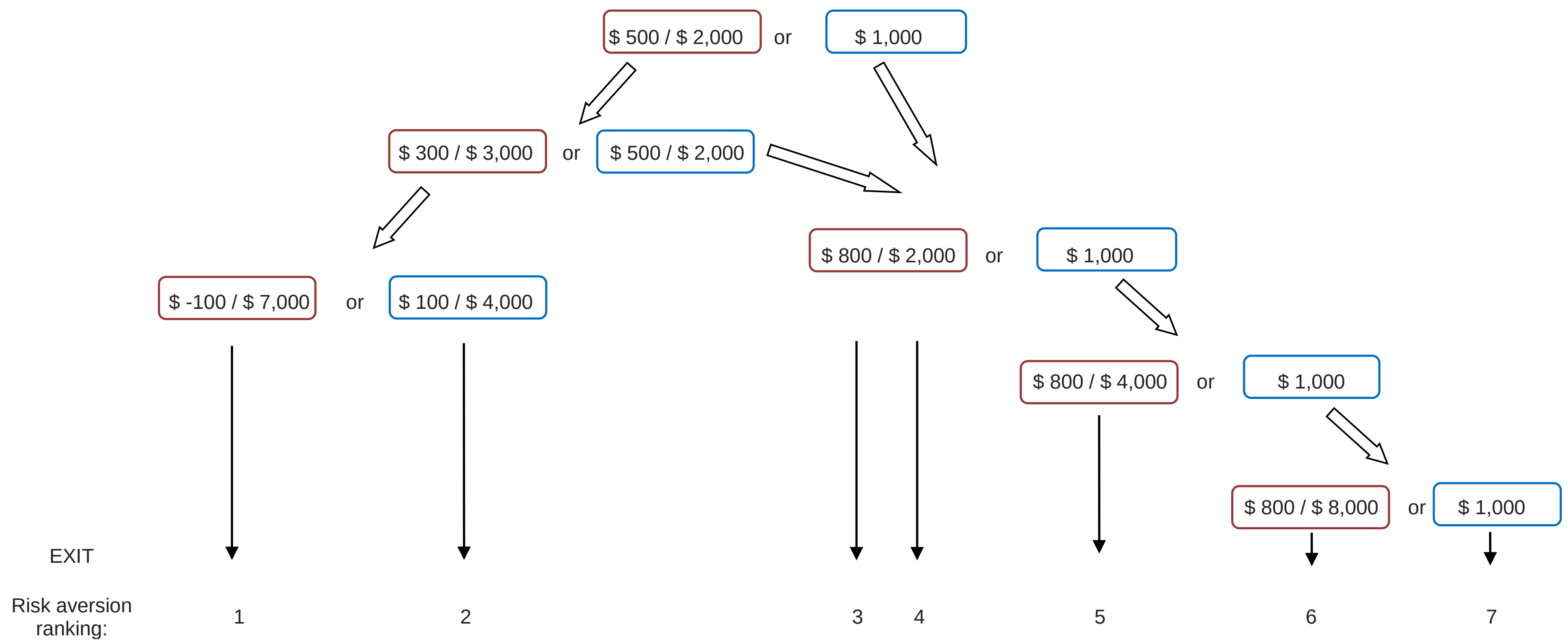
Table 7: Stratifications and heterogeneous effects

	Women		Men	
	Urban	Rural	Urban	Rural
	[1]	[2]	[3]	[4]
Panel A. Main results: Stratifications				
Homicide rate	1.46***	1.08	1.54**	1.23
	(0.48)	(0.87)	(0.71)	(0.92)
Panel B. Heterogeneous effects: Economic Resources				
Household PCE				
Homicide rate * Bottom 50% PCE	2.08***	1.12	0.91	0.92
	(0.73)	(1.21)	(0.74)	(1.29)
Homicide rate * Upper 50% PCE	1.01	1.67	2.55***	2.31**
	(0.65)	(1.05)	(0.85)	(1.09)
Education				
Homicide rate * Education: less than 9 years	0.96	0.83	1.35*	1.44
	(0.71)	(1.11)	(0.73)	(0.91)
Homicide rate * Education: at least 9 years	1.92***	2.10*	1.74**	1.74
	(0.70)	(1.13)	(0.85)	(1.66)
Panel C. Heterogeneous effects: Employment status				
Labor market participation				
Homicide rate * Does not have a job	1.78***	1.18	2.60	0.26
	(0.54)	(0.96)	(1.70)	(1.86)
Homicide rate * Has a job	1.08	2.08	1.24*	1.46
	(0.71)	(1.93)	(0.72)	(1.07)
Self-employment				
Homicide rate * Is not self-employed	1.35***	1.11	1.87**	1.85*
	(0.44)	(0.95)	(0.95)	(1.12)
Homicide rate * Self-employed	2.22	9.05***	1.45*	-0.24
	(2.53)	(3.10)	(0.82)	(1.37)
Panel D. Heterogeneous effects: Emotional well-being				
Homicide rate * Emotional well-being: lower	1.68**	1.59	2.01**	1.79
	(0.66)	(1.08)	(0.84)	(1.23)
Homicide rate * Emotional well-being: best	1.01*	0.44	1.08	0.74
	(0.53)	(1.26)	(0.82)	(1.04)
Mean dep. variable	29.58	33.09	29.21	31.90
Observations	7,794	5,924	5,006	3,972
Number of individuals	3,897	2,962	2,503	1,986

Notes: Standard errors clustered at the municipality level. *** p<0.01, ** p<0.05, * p<0.1.
In all models we control for time-varying covariates from the previous MxFLS wave, time and individual fixed effects. In models of heterogeneous effects, coviarates and time fixed effects are interacted with the binary variables capturing the heterogeneity.

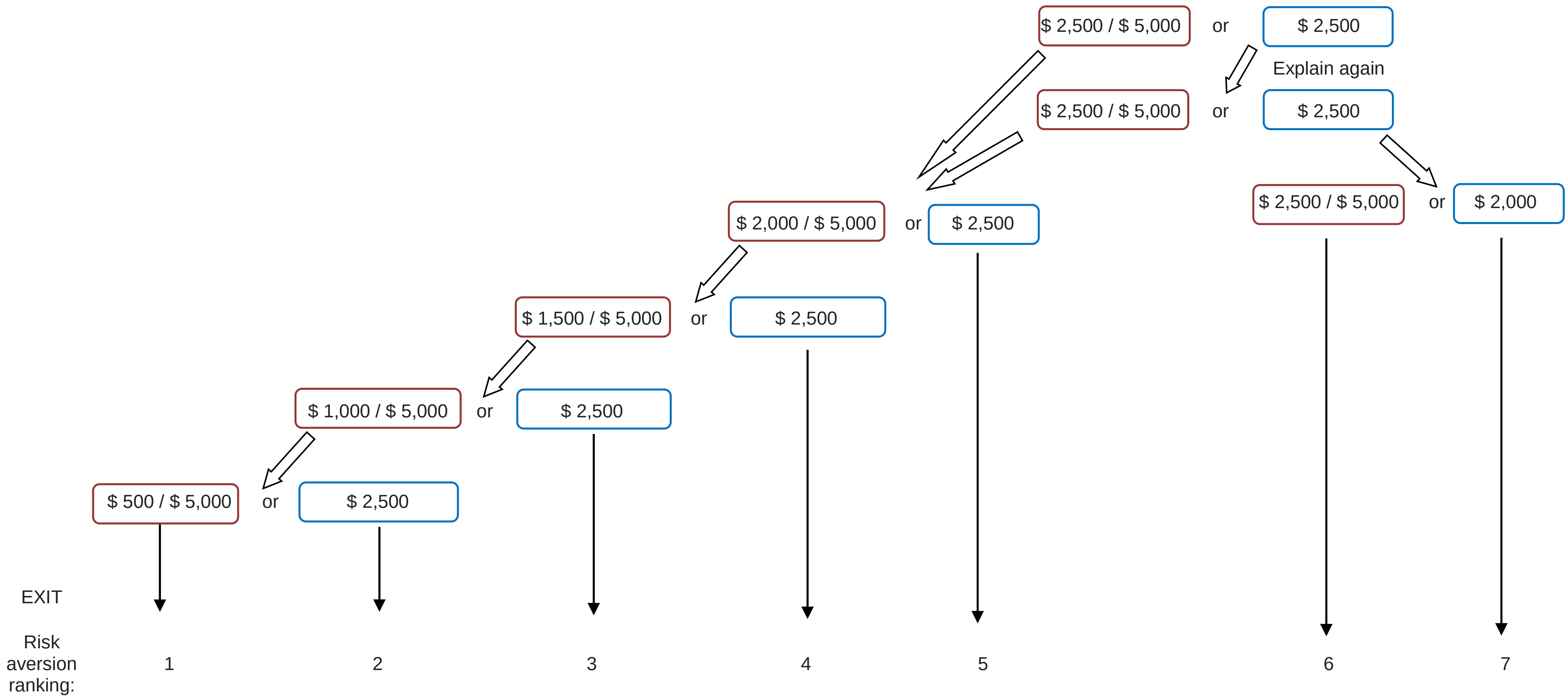
APPENDIX

Figure 1A: 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.
It is worth mentioning that it is expected that those who chose $500 / $2,000 over $1,000 in the first choice would choose $800 / $2,000 over $1,000 if faced with the decision.
We impose that for the very small percentage for whom this does not happen.

Figure 2A: 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 A1: Risk aversion index in MxFLS2 given risk aversion index in MxFLS3

Risk index in MxFLS2	Risk index in MxFLS3 1	2	3	4	5	6 (Gamble averse)	7 (Gamble av-pay)	Total
1	820	170	432	676	1,180	207	258	3,743
	32%	32%	34%	35%	34%	31%	31%	33%
2	136	25	67	86	163	37	43	557
	5%	5%	5%	4%	5%	6%	5%	5%
3	243	38	102	181	268	55	58	945
	9%	7%	8%	9%	8%	8%	7%	8%
4	938	203	456	693	1,261	250	315	4,116
	36%	38%	36%	35%	36%	38%	37%	36%
5	212	45	82	135	244	46	64	828
	8%	8%	7%	7%	7%	7%	8%	7%
6	51	12	28	29	60	9	18	207
	2%	2%	2%	1%	2%	1%	2%	2%
7	194	38	92	155	328	59	86	952
	7%	7%	7%	8%	9%	9%	10%	8%
Total	2,594	531	1,259	1,955	3,504	663	842	11,348

Table A2: "Gamble averse" and "Most risk averse" in MxFLS3

	Gamble averse-pay = 100	Gamble averse = 100	Gamble averse or most risk averse = 100	Most risk averse = 100 (excluding gamble averse)
	[1]	[2]	[3]	[4]
Female	-0.96	-0.66	1.17	1.87
	(0.60)	(0.79)	(1.30)	(1.32)
Age	0.02	-0.10	-0.34	-0.36
	(0.12)	(0.15)	(0.23)	(0.24)
Age squared	0.00	0.00	0.01**	0.01*
	(0.00)	(0.00)	(0.00)	(0.00)
Married	-0.85	-0.94	-1.20	-0.73
	(0.62)	(0.75)	(0.97)	(1.06)
Number of children	0.08	-0.02	-0.12	-0.12
	(0.18)	(0.20)	(0.30)	(0.33)
Years of education = 0	1.92	1.82	4.81**	4.56**
	(1.27)	(1.55)	(2.13)	(2.19)
Years of education = 1 to 5	0.90	0.55	1.16	0.93
	(0.90)	(1.21)	(1.60)	(1.59)
Years of education = 7 to 9	-0.33	-2.18**	-0.16	1.45
	(0.80)	(1.11)	(1.76)	(1.88)
Years of education = 10 to 12	-2.02**	-4.63***	-6.81***	-4.10*
	(0.88)	(1.20)	(2.21)	(2.25)
Years of education = 13 or more	-3.13***	-6.06***	-3.97*	0.17
	(0.83)	(1.13)	(2.11)	(2.24)
Has a job	-2.26**	-0.80	-2.32	-2.09
	(1.02)	(1.24)	(2.09)	(2.14)
Is self-employed	2.21***	1.08	3.21**	2.97*
	(0.85)	(1.15)	(1.57)	(1.70)
Earnings (quartic root)	0.13	0.10	0.05	-0.01
	(0.12)	(0.16)	(0.26)	(0.26)
HH size	0.17	-0.03	-0.42	-0.48
	(0.20)	(0.26)	(0.38)	(0.38)
Number of children other HH members	-0.10	0.16	0.96	1.03*
	(0.26)	(0.37)	(0.59)	(0.59)
HH PCE (quartic root)	-0.34	-0.73**	-1.94***	-1.72***
	(0.27)	(0.33)	(0.63)	(0.61)
Reside in rural locality	-1.52*	-0.59	2.06	2.80
	(0.90)	(1.10)	(1.76)	(1.86)
Mean of dep. Variable	7.42	13.26	44.14	35.60
Number of observations	11,348	11,348	11,348	9,843

Notes: Standard errors clustered at the municipality level. *** p<0.01, ** p<0.05, * p<0.1.
All covariates are measured at the time of MxFLS2.

Table A3: Self-reported feelings of safety from crime and homicide rates

	At time of MxFLS3			At time of MxFLS2		
	Feel less safe than 5 years ago = 100	Feel scared of being attacked during the day = 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 day = 100	Feel scared of being attacked during the night = 100
	[1]	[2]	[3]	[4]	[5]	[6]
Homicide rate change from 2005 to 2009	1.15***	0.70*	1.05***	-0.12	-0.40	-0.29
	(0.25)	(0.38)	(0.26)	(0.40)	(0.62)	(0.41)
Mean of dep. Variable	19.27	37.18	22.11	15.00	33.05	19.81
Number of observations	11,288	11,288	11,288	11,330	11,330	11,330

Notes: Standard errors clustered at the municipality level. *** p<0.01, ** p<0.05, * p<0.1.
In all models we further control for gender and time-varying covariates from the previous MxFLS wave.
There are slightly fewer observations than in our analytical sample because of missing information on self-reported feelings. of safety.

Table A4: Robustness checks

	Panel A. Most risk averse = 100 *Alternative treatments to "gamble averse"*		
	Gamble averse classified as most risk averse = 100	Gamble averse classified as most risk averse = 0	Gamble averse excluded
	[1]	[2]	[3]
Homicide rate	1.49***	1.66***	1.75***
	(0.47)	(0.45)	(0.48)
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	1.49***	1.63***	1.03**
	(0.47)	(0.53)	(0.43)
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	0.96**	1.63**	1.77**
	(0.40)	(0.77)	(0.83)
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.
We further control for time-varying covariates from the previous MxFLS wave, interview fixed effects 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)